Impact of Climate and Soil Variability on Crop Water Productivity and Food Security of Irrigated Agriculture in Northern Togo (West Africa)

PhD in Integrated Management of Water, Soil, and Waste

Faculty of Environmental Sciences,

Technische Universität Dresden (TUD)

and

Institute for Integrated Management of Resources and of Material Fluxes,

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Dissertation

by

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Submitted in October 2019

Declaration

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- When selecting and evaluating the material and also when producing the manuscript, I have received support from the following persons: Dr. Avellán Tamara (UNU-FLORES) and Prof. Dr. Niels Schütze (TU Dresden).

- No further persons were involved in the intellectual production of the present work. In particular, I have not received help from a commercial doctoral adviser. No third parties have received monetary benefits from me, either directly or indirectly, for work relating to the content of the presented dissertation.

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Place:	Date:
Dresden, Germany	6th January 2020

Agossou GADEDJISSO-TOSSOU

Dedication

I dedicate this work to my beloved:

- parents: Marcelin and Sivomé
- wife and children: Yawa, Olga, and Olivia
- siblings: Yao, Abla, Kossi, Ayaba, Akou, and Akouwa

for their love and support.

Acknowledgements

I give glory to the Almighty God whose mercy on me endures forever. My heartfelt gratitude goes to my supervisors Dr. Tamara Avellán (UNU-FLORES, Germany) and Prof. Dr. Niels Schütze (TU Dresden, Germany) for diligently supervising this study and providing encouragement all along the course of this research work. Their great scientific collaboration, constant support, guidance, and patience throughout this study are gratefully acknowledged.

I gratefully acknowledge the financial support provided by the Islamic Development Bank (IsDB), the UNU-FLORES, and the Institute of Hydrology and Meteorology (IHM) at TUD. I thankfully acknowledge the logistical assistance received from the UNU-FLORES and TUD as well as the soil laboratory facilities they provided me with. I appreciate the administration of the national meteorological service of Togo for providing us with the climate data used in this PhD research work. I thank the Togolese National Agricultural Research Institute for providing experimental facilities and advisory services on the maize cultivar used for this work.

I respectfully acknowledge Dr. Reza Ardakanian, the founding director of UNU-FLORES, Prof. Dr. Edeltraud Guenther, the current director of UNU-FLORES, Prof. Hiroshan Hettiarachi, Dr. Stephan Hülsmann, Dr. Mathew Kurian, the academic officers at UNU-FLORES for their encouragement and suggestions. Thanks are also given to Dr. Lulu Zhang and Dr. Serena Caucci at UNU-FLORES for constructive discussions during the design of the field experiment. My thanks go to Mr. Mohamad Haroun, for his constant and valuable security pieces of advice and IT assistance. I would also like to express my sincere gratitude to Ms. Julie Coulombe, Mr. Bastian Nebel, Mrs. Rachel Ahrens, Ms. Claudia Matthias, and Ms. Atiqah Fairuz Binte Md Salleh for all the logistical supports at UNU-FLORES. I am also thankful to my PhD colleagues, Andrea, Anika, Janis, Mahesh, Parvathy, Sridhar, Sekela, Solomon, and Thuy for their friendship and collaboration during these three years. I am highly indebted to Dr. Thomas Wöhling, Mr. Marius Müller, and Ms. Lisa Rommel for their valuable assistance during the soil laboratory work of this PhD research at TUD. I would like to acknowledge, with thanks, Mr. Oleksandr Mialyk for helping to do simulations with TUD high-performance computing.

Most of all, my heartfelt thanks go to my family for their patience, encouragement and support throughout this work. Particularly, I want to thank my wife, Yawa and daughters, Olga and Olivia for their understanding of not being with them all the time of this work. I am thankful to my friends, who nudged me when I needed it. I would like to thank all others who contributed directly or indirectly to the fulfilment of this study.

Abstract

West Africa is subject to frequent yield losses due to erratic rainfall and degraded soils. At the same time, its population is expected to double by 2050. This situation is alarming in northern Togo, a West African dry savannah area, where rainfed maize is a staple food. Thus, it is necessary to improve agricultural productivity, e.g., by evaluating and introducing alternative irrigation management strategies, which may be implemented in this region. For this purpose, the present investigation focused on evaluating the potential of deficit and supplemental irrigation, as well as assessing the impact of climate and soil variability on maize yield under irrigated agriculture using irrigation optimisation strategies in northern Togo. The Optimal Climate Change Adaption Strategies in Irrigation (OCCASION) framework was adapted and employed to address the research objectives. It involves: (i) a weather generator for simulating long-term climate time series; (ii) the AquaCrop model, which was utilised to simulate the irrigation during the growing periods and the maize yield response to given irrigation management strategies; and (iii) a problem-specific algorithm for optimal irrigation scheduling with limited water supply. Five irrigation management strategies viz. T1: no irrigation (NI), T2: controlled deficit irrigation (CDI) and T3: full irrigation (FI) in the wet season, T4: controlled deficit irrigation (CDI) and T5: full irrigation (FI) in the dry season were assessed regarding their impact on maize yield in northern Togo. The results showed high variability in rainfall during the wet season, which led to substantial variability in the expected yield for NI. This variability was significantly lessened when optimised supplemental irrigation management strategies (CDI or FI) were applied. This also holds for the irrigation scenarios under the dry season. Finally, these findings were validated by an irrigation field experiment conducted at an agricultural research institute in northern Togo. Under a moderate level of deficit irrigation during the vegetative and reproductive growth stages, the above-ground biomass and the maize grain yield were reduced. However, a moderate level of deficit irrigation during the vegetative growth stage could result in similar values of water productivity to that of fully irrigated treatment. It was found that, based on the values of the statistical indicators, AquaCrop has accurately simulated the maize grain yield for all the irrigation strategies evaluated. The results of this study revealed that climate variability might engender a higher variability in the maize yields of northern Togo than soil variability does. Large- and small-scale water harvesting, access to groundwater, and irrigation infrastructures would be required for implementing the irrigation management strategies assessed in this study.

List of Publications of the Thesis

1. Gadédjisso-Tossou, A., Avellán, T., Schütze, N. 2018. Potential of Deficit and Supplemental Irrigation under Climate Variability in Northern Togo, West Africa. *Water*, 10, 1803; doi:10.3390/w10121803

2. Gadédjisso-Tossou, A., Avellán, T., Schütze, N. 2020. Impact of Irrigation Strategies on Maize (*Zea mays L.*) Production in the Savannah Region of Northern Togo (West Africa). *Water SA, Accepted for publication.*

3. Gadédjisso-Tossou, A., Avellán, T., Schütze, N. Impact of climate and soil variability on maize (*Zea mays L.*) yield under full and deficit irrigation in the savannah region of northern Togo, West Africa. *In preparation for submission.*

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List of Acronyms and Abbreviations

AfDB	African Development Bank
APPM	Assessment prognoses planning and management
APSIM	Agricultural production systems simulator
AU	African Union
CDI	Controlled deficit irrigation
CSM	Crop simulation model
CWPF	Crop water production function
DAISY	Danish simulation model for transformation and transport of energy and matter in the soil plant atmosphere system
DSSAT	Decision support system for agrotechnology transfer
ECA	Economic Commission for Africa
ET	Evapotranspiration [L] or [L^3]
FAO	Food and Agriculture Organization of the United Nations
FI	Full irrigation
GCM	General circulation model
GET-OPTIS	Global Evolutionary Technique for Optimal Irrigation Scheduling
ICAT	Institut de Conseil et d'Appui Technique
IPCC	Intergovernmental Panel on Climate Change
ISP	Integral suspension pressure method
ITRA	Institut Togolais de Recherche Agronomique
IWRM	Integrated water resources management
LARS-WG	Long Ashton research station- weather generator
MIFA	Mechanism for promoting agricultural financing in Togo
NI	No irrigation
OCCASION	Optimal Climate Change Adaption Strategies for Irrigation
RCM	Regional climate model
SCWPF	Stochastic crop water production function
SOC	Soil Organic Carbon
SSA	Sub-Saharan Africa
TFP	Total factor productivity
WGEN	Weather generator

1. Introduction

1.1 Background and Problem Statement

1.1.1 Global Fresh and Agricultural Water Use

Water is a critical natural resource upon which all social and economic activities and ecosystem functions depend (WWAP, 2012). Globally, water withdrawal and consumptive water use—water removed from available supplies without return to the original water resource system—respectively increased from ~ 1,000 and ~ 2,000 km^3/year in 1979 to ~ 1,500 and ~ 3,300 km^3/year in 2010. This increase is primarily driven by growth in the agricultural sector (mostly irrigation), accounting for as much as 80 % of the total water withdrawals (Wada, Wisser and Bierkens, 2014). As the world population reaches 9 billion people in 2050 and economic growth increases the consumption of food and manufactured goods, the trends towards increasing demand for water from all sectors are projected to continue in the coming decades (FAO, 2013). Other estimates present the proportion of the African population at risk of water scarcity—the volumetric abundance, or lack thereof, of water supply. This is typically computed as a ratio of human water consumption to available water supply in a given area (Schulte, 2014) and stress—the ability, or lack thereof, to meet human and ecological demand for water (Schulte, 2014)—increasing from 47% in 2000 to 65% in 2025 (Ashton, 2002). By 2025, in twelve countries in Africa (mainly in West Africa), the population at risk of water stress—total water withdrawals over available renewable supply—is estimated to be 460 million people (Bates *et al.*, 2008).

FAO (2011) pointed out that, based on existing trends in agricultural water productivity and yield gains, the agricultural withdrawals will need to increase to more than 2,900 km^3/year by 2030 and almost 3,000 km^3/year by 2050. This indicates a net increase of 10% between now and 2050. Water and agriculture are inextricably interconnected. In Africa, agriculture employs 65% of Africa's labour force, accounts for 32% of total gross domestic product (Chauvin, Mulangu and Porto, 2012) and contributes to 60–70% of export earnings and employment (Breman, Groot and van Keulen, 2001). Despite its high contribution to the overall economy, agriculture in Africa faces numerous obstacles, including water-related challenges.

Water is the primary channel through which the impacts of climate change—especially, on the world's ecosystems and the livelihoods of societies—will be felt. Every element in the water cycle will be impacted by climate change (UN-Water, 2010). Since the 1950s, many of the recorded changes due to the warming of the climate system are unprecedented over decades to millennia (UN-Water, 2010). Climate change over the 21st century is expected to lessen renewable surface water and groundwater resources in most arid and semi-arid regions, increasing competition for water among sectors (IPCC, 2014). West Africa's water resources are characterised by extreme variability over both space and time. They are highly vulnerable to climate variability, as illustrated by the disastrous impact of meteorological and agricultural droughts over the past 30 years (ECA, AU and AfDB, 2003). Since the 1970s in the tropics and sub-tropics, droughts have become more common (Bates *et al.*, 2008). Several severe and prolonged droughts events were noted in the recent past, such as the 1970s and 1980s droughts in the Sahelian area of West Africa (Masih *et al.*, 2014).

1.1.2 Erratic Rainfall, Rising Temperatures, and Soil fertility depletion in West Africa

The predominance of rainfed agriculture in Africa is another critical challenge to the crop production sector. Ninety-five per cent of sub-Saharan Africa's farmland relies on rainfed agriculture (Wani *et al.*, 2009), making most people heavily dependent upon each year's rainfall pattern (UNEP, 2010). Rainfall in Africa is a very crucial factor in the ability of farmers and herders to produce the foodstuffs they need to feed their families and their population (Glantz, 1992). Similarly, De Wit *et al.* (1978) pointed out that the relation between water consumption and crop yield is a straightforward and amazingly linear one that hold across scales, from plant to field to the district, provided that no very severe water stresses occur. However, in West Africa, especially in the Sahel region, the amount of rainfall has reduced over decades (Hulme, 2001). Glantz (1992) contended that in sub-Saharan Africa evapotranspiration rates would increase, which could be troublesome in areas where evaporation rates are marginally in balance with precipitation. Such an increase could create moisture stress in certain plants, necessitating, as one possible alternative, a need for supplemental water supplies in response to decreases in soil moisture. Also, Turral *et al.* (2011) indicated that an increase in temperatures might trigger increased demand for water by crops and natural vegetation through evapotranspiration and lead to a more rapid reduction of soil moisture.

It is known that soil fertility is not a static feature. It changes continuously, and its status is determined by the relationship between physical, chemical, biological, and anthropogenic processes (Smaling, Nandwa and Janssen, 1997). Soil fertility in Africa is under pressure as an increasing number of farmers attempt to make a living based on what the land can offer to grow plants. The magnitude of nutrient depletion in Africa's agricultural land is colossal (Smaling, Nandwa and Janssen, 1997). FAO (1995) disclosed that Africa is now losing 4.4 million tons of Nitrogen, 0.5 million tons of Phosphorus, and 3 million tons of Potassium every year from its cultivated land. Africa's annual fertiliser consumption is several times lower than these rates. Soil fertility depletion is the main biophysical factor limiting crop production in many African smallholder farms (FAO, 1995). In other words, the use of mineral fertilisers by many smallholder farmers remains low because of socioeconomic constraints. This suggests that locally available organic materials will continue to be used as sources of nutrients. However, the sources of organic manure are limited in most African countries (Smaling, Nandwa and Janssen, 1997). This situation of soil fertility decline is more pronounced in sub-Saharan Africa (SSA). Rockström and Barron (2007) pointed out that yield response to rain is only achieved through proper soil fertility management. It should be noted that soil heterogeneity results in variable responses of crops to fertilisers within single farms (Tittonell *et al.*, 2008). These scenarios, combined with changes in rainfall patterns, may lead to more frequent crop failures.

1.1.3 Transboundary Water Issues in West Africa

Transboundary water resources management is problematic because of the lack of coherent arrangements for sharing of said resources. About 40% of the world's population lives in transboundary river basins, and more than 90% live in countries with basins that cross international borders (Sadoff and Grey, 2005). Ashton (2002) asserted that some 85% of Africa's water resources are comprised of large river basins that are shared between several countries. Around 76% of sub-Saharan Africa falls within 53 international river basin catchments crossed by multiple borders (World Bank, 2011) viz. the Niger basin, Volta basin, Lake Chad basin, and the Nile basin, among others. This has generated conflicts over water, particularly in arid and semiarid regions. Moreover, the lack of sufficient water infrastructure can increase the inability of the population in Africa to harness these resources. WWAP (2015) reported that, currently, only 5% of Africa's potential water resources are developed and average per capita storage is 200 m^3 versus 6,000 m^3 in North America. Only 5% of Africa's cultivated land is irrigated, and less than 10% of the hydropower potential is utilised for electricity generation (WWAP, 2015). Due to a lack of water supply and delivery infrastructures, the full potential of water resources has not been realised, especially in West African countries (Njuki and Bravo-Ureta, 2016).

1.1.4 Agriculture and Water Use in Togo

Togo is a small West African francophone country. It is bordered by Burkina Faso and the Atlantic Ocean in the north and south, respectively. Togo is bordered in the west by Ghana and in the east by Benin. According to the Togolese Ministry of the Environment and Forestry (MERF, 2009), in the dry savannah of northern Togo, the rainy season which spanned six months in the 1970s, is reduced to five or four months nowadays. Thus, on the one hand, a significant amount of rainwater falls within a short period causing flooding, while, on the other hand, frequent dry spells in the rainy season will lead to crop failure (Mcsweeney, New and Lizcano, 2009). Also, there is no rainfed agricultural activity during the dry season in northern Togo due to a lack of rainfall (Ogounde and Abotchi, 2003). The Togolese National Agricultural Research Institute (ITRA) (2008) and Didjeira *et al*. (2007) have recognised maize as the staple food in Togo, as it represents 60% of the cereals consumed by the Togolese population. In northern Togo, to provide maize throughout the year, some farmers are growing it under limited irrigation in the dry season. These farmers obtain little help from the scientific research community. The correct application of limited irrigation requires a thorough understanding of the crop parameters and yield responses to water. However, this issue has not yet been accorded particular attention in northern Togo.

In a nutshell, the low agricultural productivity of smallholder farmers in northern Togo, West Africa may be attributed to the erratic rainfall, recurrent meteorological and agricultural droughts, limited availability of good quality soil and water resources. WWAP (2015) reported that a sound, systematic knowledge of the integrated water resource management approach considering both surface and groundwater is imperative for effective use of water. Schütze and Schmitz (2010) disclosed that a high crop-water productivity is the prerequisite for sustainable agricultural production with limited water resources in arid and to some extent in semi-arid zones. Also, Molden *et al*. (2010) pointed out that increasing the productivity of water in agriculture will play a vital role in reducing competition for scarce resources, prevention of environmental degradation and provision of food security. It can be noted that introducing irrigation in the dry season in northern Togo is a panacea to the challenges mentioned above regarding the low agricultural productivity. However, there is a lack of knowledge about climate and soil variability of northern Togo and its effect on crop yield for the dry season irrigation implementation.

1.2 Objectives of the Study

The research questions which arise from the paragraphs above are (i) Which reasonable irrigation and crop models can be used to assess maize crop response to water in West Africa, given the paucity of data in the area? (ii) What is the potential of deficit and supplemental irrigation for maize in northern Togo? (iii) To what extent climate and soil variability are affecting maize yield in northern Togo? Thus, the present study aims at answering these questions.

The overall objective of this study is to evaluate crop response under irrigation to the soil and climate variability of a specific site in northern Togo, West Africa.

The specific objectives of the study are:

(i) to identify a reasonable crop water model which can be applied in the context of the paucity of data in the region to assess maize response to water;

(ii) to assess the potential of deficit and supplemental irrigation for maize in northern Togo;

(iii) to validate a reasonable irrigation schedule of maize for a specific site in northern Togo considering soil and climate variability.

This thesis is composed of four further chapters. Chapter 2 presents an overview of the state of the art of the agroecosystems, farming systems and irrigation management, the factors influencing crop water productivity and the models used to assess it in West Africa and identifies the research gaps. Chapter 3 covers the workflow of this study, while chapter 4 provides an overview of the publications which originated from this investigation. Chapter 5 concludes this study and gives an outlook of further work.

2. State of the Art

2.1 Relevant Agroecosystems, Farming Systems and Irrigation Management in West Africa

Swift *et al*. (1996) defined agroecosystems as: "the ecosystems in which humans have exerted a deliberate selectivity on the composition of the biota, i.e., the crops and the livestock maintained by the farmer, replacing to a greater or lesser degree the natural flora and fauna of the site." Diversification of agroecosystems such as complex crop rotations, cover crops, and integrated crop-livestock can engender greater opportunities and higher incomes for farmers (Ghosh, Sarkar and Roy, 2014; Alhameid *et al.*, 2017). In West Africa, farming systems are highly diverse and characterised by the following traits (Table 1).

Table 1. Principal common characteristics of small-scale farming systems in West Africa

No	Traits	Examples
1	Small land area	0.5 to 5 ha
2	Diverse production goals	Feeding the family, meeting social obligations, achieving a target income
3	Communal responsibilities	Communal labour
4	Limited market access	Poor roads and insufficient transport
5	Poor infrastructure	Most roads, schools, etc., provided by farmers themselves
6	Diminishing resource base	High population pressure, decrease of the fallow period
7	Major constraints	Unavailability of fertilisers and pesticides, uncertain policy environment, fragile soils, high pest potential
8	Vicious circle of poverty	Unsustainable agriculture practices

Source: Adapted from Izac and Swift (1994)

The application of agroforestry systems in the tropics contributes to store high biomass for soil fertility replenishment and offers the potential for carbon stock and sequestration potential in smallholder agroecosystems (Thangata and Hildebrand, 2012). Another way of improving the crop yield is to adopt irrigation management strategies in the agroecosystems.

FAO (2005) reported that numerous countries in Africa consider water and irrigation management as a critical factor in improving their food security and to ensure access to drinking-water for their populations. The two trends confirming net progress in water management in African countries are integrated water resources management (IWRM) and the development of small-scale irrigation (UN Environment, 2018). The former is adopted in a few countries in West Africa while the latter is the primary type of construction retained by countries still trying to develop their irrigated area (UN Environment, 2018). It envisages management by the users and their more active participation, and it often goes hand in hand with the introduction of lower-cost technologies such as flood (gravity or pumps), drip, watering can. Table 2 below depicts the different types of irrigation systems used by farmers in West Africa.

Table 2. Typology of irrigation systems in West Africa

No	Typology	Characteristics
1	Traditional irrigation	Watering cans are used.
2	Lift irrigation by direct pumping	Small pumps are used to pump water from rivers, streams or shallow wells for direct irrigation.
3	Tube well irrigation	Wash bore and shallow tube well irrigation.
4	Diversion of flood control irrigation	Water is diverted from streams or floodwater is controlled for irrigation.
5	Formal irrigation	The irrigation area is equipped with the necessary irrigation structures. The system is usually managed by government agencies, private companies, individual farmers or groups of farmers. The irrigated area may be large, medium or small. It consists of sprinkler and drip irrigation.

Source: Adapted from Nwa (2003)

Sub-Saharan Africa has a huge potential for irrigation expansion mostly through large multi-purpose projects (You, 2008); it uses just around 2% of its water resources in irrigation compared to 36% in South Asia and 53% in the neighbouring East/North Africa regions (Faurès, Hoogeveen and Bruinsma, 2002). In sub-Saharan Africa, arable lands under irrigation are equal to 6% of the total cultivated area compared to 37% in Asia, 14% in Latin America (Waltina, Houdret and Brüntrup, 2017). It must be emphasised that almost all West African countries, except Cape Verde, reported the existence of a significant irrigation potential that is yet to be tapped. Thus, these countries have elaborated irrigation policies, strategies and plans to realise this potential, except for the post-conflict countries which are relatively rich in water resources, such as Sierra Leone and Liberia (Namara and Sally, 2014). However, most of this potential may have little benefit and use for smallholder communities spread here and there in the same country. It is difficult to have large irrigated areas for such communities.

2.2 Key Performance Indicators: Water productivity and Food Security

Crop water productivity is defined in different ways by different researchers (Bessembinder *et al.*, 2005). Molden (1997) introduced the term water productivity and argued that it could either be related to the physical mass of production or the economic value of production per unit volume of water. This term has several meanings: more kilograms per unit of evapotranspiration (ET) for some people, more production per unit of irrigation water applied for others or more welfare per drop of water consumed in agriculture for others (Molden *et al.*, 2003). Water productivity with dimensions of kg m^{-3} is defined as the ratio of the mass of marketable yield to the volume of water consumed by the crop (Geerts and Raes, 2009). Moreover, in defining crop water productivity, Perry *et al.* (2009) argued that we need to be specific in indicating which product (biomass or yield) and which consumption (transpiration or evapotranspiration) we are stating. Water productivity can also be defined as: "the ratio of the net benefits from a crop, forestry, fishery, livestock and mixed agricultural systems to the amount of water used to produce those benefits" (Molden *et al.*, 2010). Recently, Brauman *et al.* (2013) defined crop water productivity as food kilocalories produced per litre of evapotranspiration. It is essential to know the methods that have been used to evaluate crop water productivity.

How the world will feed itself is one of the most complicated unsolved problems of sustainable development. However, many people thought it had been resolved with significant breakthroughs in food productivity based on scientific advances (Sachs, 2015). Food security is defined as: "Food security exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food which meets their dietary needs and food preferences for an active and healthy life" (FAO, 1996). This definition described the four pillars of food security viz. accessibility, availability, utilisation, and stability. Ericksen *et al.* (2011) highlighted SSA as a hotspot of food insecurity considering these all the pillars. The food security situation is worsening in SSA due to global economic conditions and weak commodity prices (FAO and ECA, 2018). By 2050, food demand is projected to increase by 60% worldwide and by over 300% in SSA due to its fast increasing population (Van Ittersum *et al.*, 2016). It should be stressed that climate change is a present and growing threat to food security and is a particularly severe threat to countries which economy is predominantly based on agriculture such as West Africa (FAO and ECA, 2018). This study focused on the availability and stability pillars of the food security concept.

2.3 Common Approaches Used to Evaluate Crop Water Productivity

Several approaches for evaluating crop water productivity have been reported in the literature. First, some researchers utilised stochastic frontier production function models to assess the technical efficiency of components of productivity. This can concern a single input or total output (Aigner, Lovell and Schmidt, 1977; Karagiannis, Tzouvelekas and Xepapadeas, 2003; Henderson *et al.*, 2016). These models are based on econometrics. Also, they mostly include socio-economic variables as inputs. Socio-economic variables are related to human behaviour. This is an essential source of uncertainties in the stochastic frontier production function models.

Second, others used total factor productivity (TFP), which can be computed by dividing a weighted average of output quantities by a weighted average of input quantities (O'Donnell, 2016). Then, partial factor productivity can be derived from the latter (Njuki and Bravo-Ureta, 2016). Like the stochastic frontier production models, the TFP consists in computing econometric regressions. The shortcomings of these models include the fact that the value zero is placed on the goods or services that have no market price. In addition, there are many assumptions regarding the behaviour of the dependent and the explanatory variables in the models. Here also, the inputs variables are mostly socio-economic ones. This is a source of bias or uncertainty in the assessment.

Third, another group of researchers employed a single factor productivity method to evaluate crop water productivity. In this method, the emphasis is put on one input factor. Many studies (Geerts *et al.*, 2009; Khaledian *et al.*, 2009; Mimi and Jamous, 2010; Mailhol *et al.*, 2011; García-Vila and Fereres, 2012; Maniruzzaman *et al.*, 2015; Chimonyo, Modi and Mabhaudhi, 2016; Dokoohaki *et al.*, 2016; Jiang *et al.*, 2016; Manevski *et al.*, 2016) tried to analyse the possible impacts of climate variability and water scarcity on the potential yield using mechanistic crop growth models such as DSSAT (Jones *et al.*, 2003), AquaCrop (Hsiao *et al.*, 2009; Raes *et al.*, 2009; Steduto *et al.*, 2009), DAISY (Hansen *et al.*, 1990), CropWat (Smith, 1992), APSIM (Keating *et al.*, 2003) or PILOTE (Mailhol, Olufayo and Ruelle, 1997). These models are process-based. They do take into consideration the soil-plant-atmosphere continuum. So, the outputs of these models are more realistic than the non-process-based model described in the two paragraphs above.

2.4 Key production Factors: Climate, Soil and Management

Progress in technology made possible the development of simple and complex crop simulation models (CSM). The main point to consider is, therefore, the availability of information needed to run the models (Basso, Cammarano and Carfagna, 2013).

Murthy (2004) pointed out that CSMs require reliable and complete meteorological data. Meteorological stations may not fully represent the weather at a chosen location. In some cases (e.g., West Africa), data may be available for only one (usually rainfall) or a few parameters (rainfall and temperature). However, solar radiation data, which is essential in the estimation of photosynthesis and biomass accumulation, may not be available. Sometimes, records may be incomplete, and gaps may have to be filled. Weather generators can contribute to filling these data gaps and generating long-term data sets.

A stochastic weather generator produces synthetic long-term time series of weather data for a location considering the statistical traits of observed weather at that location (Murthy, 2004). Two basic types of stochastic weather generator were reported in the literature. These are "Richardson" (Richardson, 1981; Richardson and Wright, 1984) and "serial" (Racsko, Szeidl and Semenov, 1991; Semenov and Barrow, 1997; Semenov *et al.*, 1998) types. On one hand, Murthy (2004) added that in a "Richardson" type of weather generator (e.g., WGEN), precipitation occurrence is modelled using a first-order two-state Markov procedure, which describes two precipitation classes (i.e., wet or dry) and considers precipitation occurrence on the previous day only. Murthy (2004) stated that Richardson-type weather generators failed to adequately describe the length of wet or dry series (i.e., persistent events such as drought or prolonged rainfall). Because the occurrence of dry spells during some particular phases of the crop development may result in crop failure, the length of wet or dry series is important for agriculture. On the other hand, to address this challenge, serial approach to weather generation was developed. In this type of weather generator, the first step in the process is modelling of the sequence of dry and wet series of days (Murthy, 2004). The amount of precipitation and the remaining climate variables are then generated dependent on the wet or dry series. The serial-type weather generator, first developed by Racsko *et al*. (1991), has been substantially updated (Semenov *et al.*, 1998) (e.g., LARS-WG).

Fairhurst (2012) reported that during the past three decades, the understanding that underpins nutrient management in cropping systems in SSA, particularly in West Africa, has undergone substantial change due to improved knowledge, based on extensive field research as well as changes in the overall social, economic and political environment (Table 3). In the 1960s and 1970s, a major consideration was given to the use of mineral fertiliser to achieve proper crop nutrition and improved crop yields. However, in the 1980s, the use of organic resources was considered because of limited access to the mineral fertilisers in West Africa during that period. Currently, many studies have highlighted the importance of using mineral fertilisers and organic resources together in ways that are adapted to local conditions to reach reasonable crop yields and efficient fertiliser use (Fairhurst, 2012).

Table 3. Changes in the proposed tropical soil fertility management paradigms over the past five decades in West Africa

Period	Approach	Role of fertiliser	Role of organic inputs	Experience
1960s to 1970s	External input use	Use of fertiliser alone thought sufficient to improve and sustain yields	Organic resources play a minimal role	Limited success due to shortfalls in infrastructure, policy and farming systems
1980s	Organic input use	Fertiliser plays a minimal role	Organic resources are the principal source of nutrients	Limited adoption. Organic matter production requires livestock ownership, excessive land and labour
1990s	Combined use of fertiliser and organic residues	Fertiliser use is crucial to lessen the main nutrient constraints	Organic resources are the major 'entry point' to soil fertility improvement and serve other functions besides nutrient supply	Localised adoption around specific crops
2000s	Integrated Soil Fertility Management	Fertiliser is a major entry point to increase yields and supply needed organic resources	Organic resources can improve the use efficiency of fertiliser	Goal of large-scope adoption

Source: Fairhurst (2012)

The pressure of the fast-increasing population has induced a shift from the prevailing fallow farming system towards permanent cultivation of the land, leading to chemical depletion of soils in West Africa (De Ridder *et al.*, 2004). The population pressure in West Africa led to the cultivation of marginal lands that are susceptible to erosion, hence, enhancing environmental degradation through soil erosion and nutrient mining (Bationo *et al.*, 2007). As a result, the increase in yield has been more due to land expansion than to crop improvement or water management potential. The soils are intrinsically low in soil organic carbon (SOC) in many parts of West Africa agro-ecosystems—except the forest zone—(Bationo *et al.*, 2007). This is due to the low shoot and root growth of crops and natural vegetation, the rapid turnover rates of organic material (Bationo *et al.*, 2007; Traoré *et al.*, 2015). It should be emphasised that organic fertilisers such as manure and crop residues are the keys to improving soil fertility in semiarid West Africa. Sources of organic fertiliser, such as manure, however, are severely limited in most of semi-arid West Africa (Shapiro and Sanders, 1998). It is also observed that in West Africa, the manure is available in sufficient amount only for areas surrounding the family compounds, and the crop residues are mostly used as feed, fuel, and building materials.

2.5 Crop Yield Modelling

Motha (2011) defined models as mathematical equations describing the relationships between crop growth, yields, technology, and climate. For instance, crop yield is a function of complex interactions of biotic and abiotic factors such as crop management, soil and field characteristics—drainage, topography, and soil water holding capacity—and weather conditions—temperature, precipitation, and light use efficiency. In other words, Murthy (2004) added that a model is a schematic representation of the conception of a system or a set of equations, which characterises the behaviour of a system. Dourado-Neto *et al.* (1998) noticed that models could be a prototype, a simplified representation, as well as an abstraction of a reality or a system. Basso *et al.* (2013) pointed out that models can be broadly classified into two general groups: deterministic and stochastic.

The stochastic frontier production models are not process-based. They are empirical models which describe the relationships among variables without referring to the processes that correlate them. So, they do not take into consideration the soil-plant-atmosphere continuum in assessing the productivity of crop water in agriculture. Unlike the econometric models, the mechanistic crop models do consider the soil-plant-atmosphere continuum in the assessment. However, most of the deterministic crop models do not consider climate change scenarios for the future assessment of crop water productivity in a specific region. Conversely, the OCCASION framework included climate variability and changes component and simulated the future crop water productivity based on climate change scenarios with a mechanistic crop model. In crop yield simulation assessment, uncertainty may arise because of spatial variability of soil properties, and other abiotic and biotic factors not considered in a deterministic model. Soil properties are subdivided into small homogenous units, and the results using deterministic models are aggregated to represent the entire field yield in order to overcome some of the problems with spatial soil variability (Basso, Cammarano and Carfagna, 2013). Still, these models failed to consider the spatial variability of the soil variability. It is well known that on a crop field, soil characteristics vary from an inch to another one. However, the spatial variability of the soil characteristics is missing in the assessment of the crop yield. Therefore, it is worth evaluating the impact of the spatial variability of soil properties on crop yield in a specific site.

2.6 Integrated Modelling

Recently, Schütze and Schmitz (2010) used DAISY (Hansen *et al.*, 1990), a model which simulates crop production and crop yield, to evaluate the potential maize (pioneer variety) yield in the function of water at an experimental site in southern France. This study was undertaken to validate a stochastic framework for decision support for optimal planning and operation of water supply in irrigation in the context of climate change. Unlike the traditional models mentioned above, Schütze and Schmitz (2010) include the Global Evolutionary Technique for OPTimal Irrigation Scheduling (GET-OPTIS) to solve the irrigation optimisation problem. Besides, DAISY mechanistic crop growth model was the central part of the OCCASION framework these authors used to derive the stochastic crop-water production functions as results of their study. The outputs include future scenarios of crop water productivity for decision-makers based on climate change uncertainties. Equally, Grundmann *et al*. (2012) used the same framework when they proposed the integrated Assessment Prognoses Planning and Management (APPM) as a tool for optimal sustainable water resources management and long-term planning in a changing arid environment. Kloss *et al*. (2012) assessed the performance of the crop models CropWat, PILOTE, Daisy, and APSIM as part of the stochastic OCCASION framework. As a result, the studies mentioned above obtained stochastic crop water production functions (SCWPFs), which can be utilised as basic tools for evaluating the impact of water stress and climate variability on the potential yield. These authors failed to consider soil variability in their investigations.

Deficit irrigation serves as a strategy to improve the overall irrigation water productivity in the water-scarce areas of West Africa (Geerts and Raes, 2009). Schütze (2012) pointed out that it is essential to find an ideal irrigation schedule under which crops can withstand an acceptable degree of water deficit and yield reduction in order to apply deficit irrigation. To date, mostly open-loop control techniques are applied for providing optimal schedules which maximise yield (Schütze, 2012).

Open-loop optimisation is based on forecasts generated by simulation or analytic functions (Shani, Tsur and Zemel, 2004) of the water budget and crop production of an irrigation system for an entire growing period in advance (Schütze, De Paly and Shamir, 2012). Optimal open-loop control leads in general to a mixed-integer optimisation challenge which is hard to address, since the number of decision variables (i.e. the number of irrigation events) is a priori unknown (Schütze, 2012). For this reason, recent studies tend to shorten the optimisation problem either by fixing the irrigation dates or the irrigation intervals. Beside these approaches, heuristic optimization algorithms, where used like Nelder–Mead simplex method (Shang and Mao, 2006) or simulated annealing (Brown *et al.*, 2006), which may fail in practice when: (i) local optimal solutions exist, or (ii) the number of decision variables becomes too large, or (iii) they require unreasonable computation power and time using brute-force approaches (Schütze, De Paly and Shamir, 2012). Finally, to avoid the problems mentioned above, a new evolutionary algorithm was developed by Schütze *et al*. (2012). It reduces the computational effort for calculating the optimal schedules considerably. This evolutionary optimisation algorithm disregards the influence of the stochastic characteristics of the pertinent climate factors (e.g., precipitation and temperature) and of the soil characteristics, which restricts their applicability (Schütze, De Paly and Shamir, 2012). Thus, it is worth adapting and applying the OCCASION in water-scarce areas of West Africa to improve the crop water productivity.

Considering the current state of the art described above, to achieve the objectives of this study, I followed three subsequent phases. The first phase was the pre-assessment based on existing data and information in the literature, which yielded the first research paper of this study. In the second phase, I did a field experiment to collect data for model calibration and validation. The second research paper of this study was written based on this field experiment. The last phase was the model calibration and a comprehensive assessment of the crop response to climate and soil variability. The outputs of this phase were the third research paper of this study. These three phases constitute the workflow of this study, which was described in detail in the following chapter.

3. Novel Framework for Optimising Irrigation Systems in West Africa

To achieve the objectives described in the introduction chapter of this study, I devised a novel framework for optimising irrigation systems in West Africa. This required the following three subsequent phases: (i) Model-based sensitivity analysis of climate and management impacts on crop water productivity, water demand and food security. The first research paper of this study resulted from this phase; (ii) Experimental validation of the farm model and management strategies, soil data analysis and modelling. The second research paper originated from this phase; and (iii) Joint stochastic analysis of the impact of climate and soil variability on crop water productivity and Food Security of Irrigated Agriculture in West Africa. The third research paper of this study was the outputs of this phase.

3.1 Model-based Sensitivity Analysis of Climate and Management Impact on Crop Water Productivity, Water Demand and Food Security

The OCCASION-framework (Figure 1) developed by Schütze and Schmitz (2010) was used as the backbone of the methodology applied in this study. It consists of (i) a weather generator that provides a statistically sound number of site-specific climate time series, (ii) a problem specific algorithm for optimal irrigation scheduling under limiting water supply, and (iii) a crop model for simulating plant growth and water consumption. This framework was adapted and used in the present study by utilizing the AquaCrop model for simulating the crop growth and water consumption. As illustrated in Figure 2, the initial phase of this study consisted in using Long Ashton Research Station-Weather Generator (LARS-WG) to generate long term time series data from observed climate data. These generated climate data combined with soil and crop data retrieved from the literature were utilised to run the modified OCCASION-framework. The outputs include the potential yields, the volume of water used to achieve them and an optimised irrigation schedule for maize cultivation in the study site. The first phase of the workflow contributed to address the specific objectives 1 and 2 of this study. This phase of the workflow was described in detail in the first research paper of this study in the following chapters.

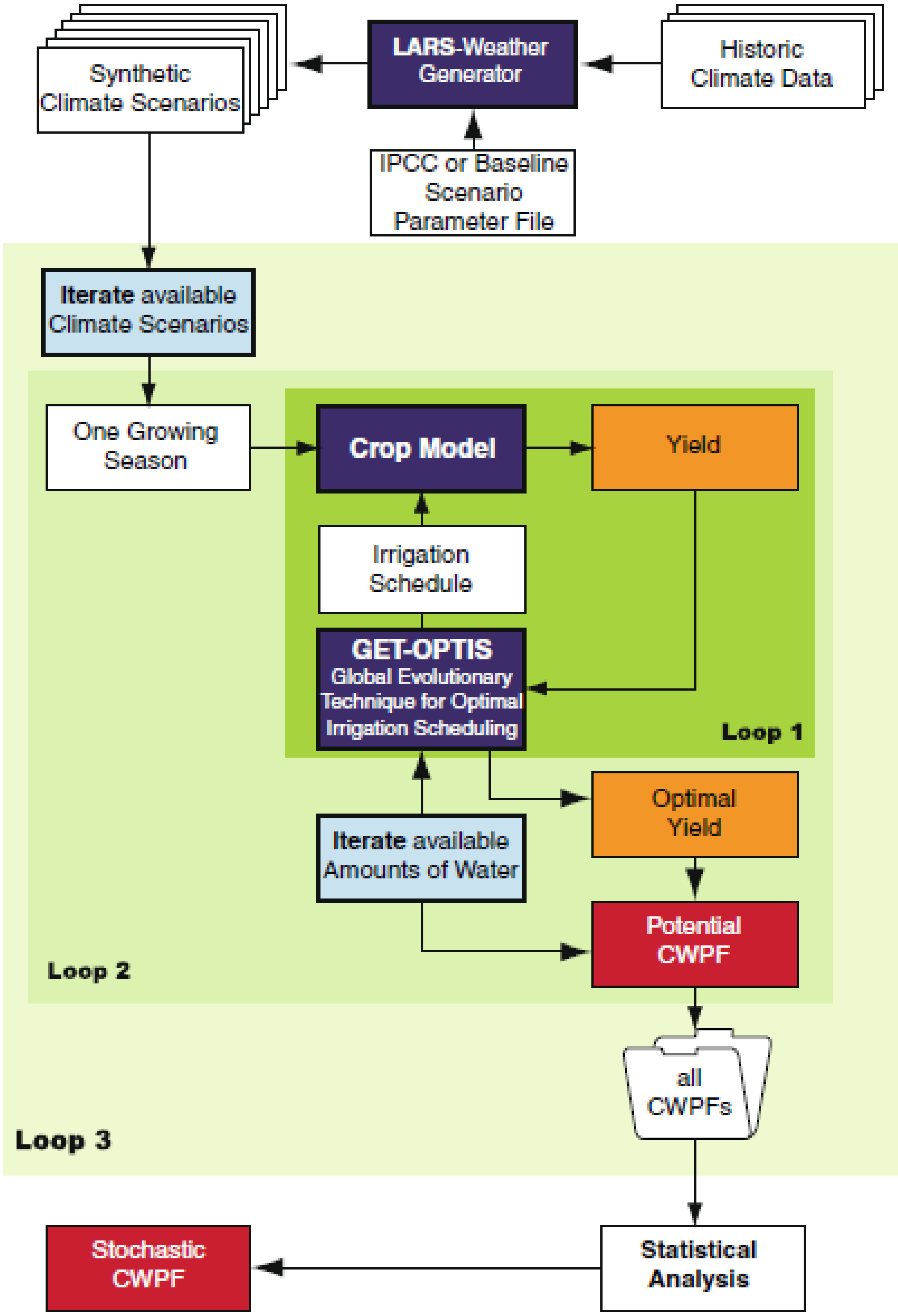

Figure 1. OCCASION-framework for generating stochastic crop water production functions (Schütze and Schmitz 2010)

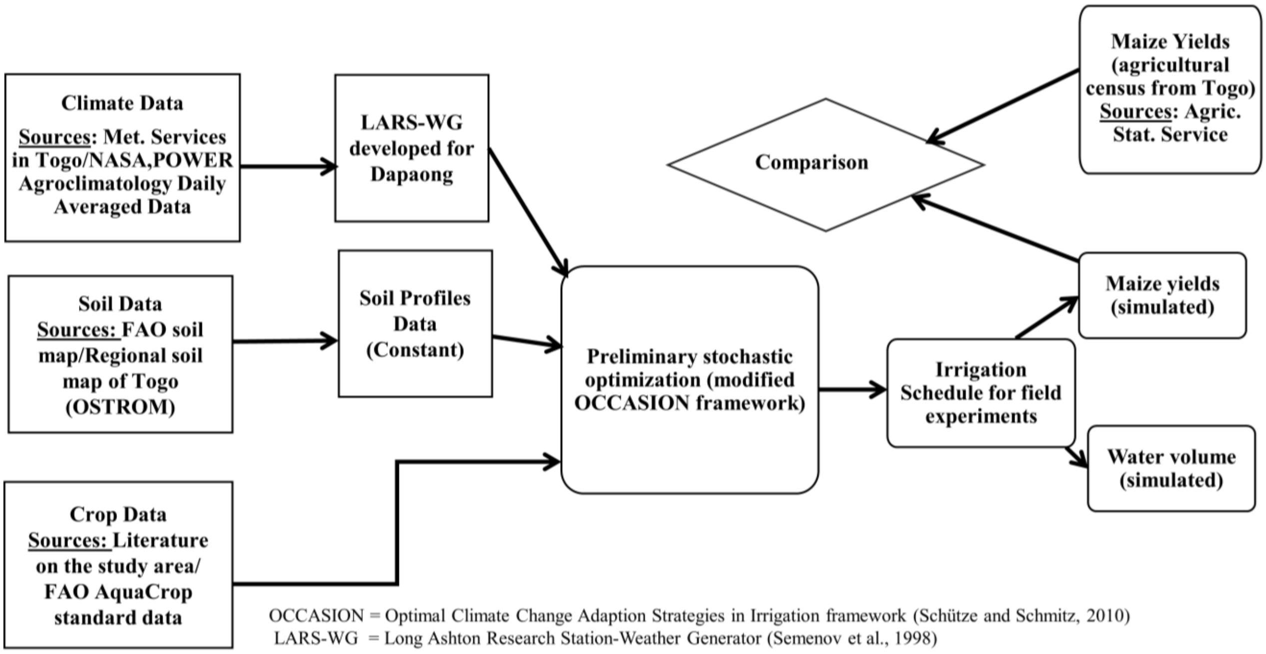

Figure 2. Initial phase: before the field experiment

3.2 Experimental Validation of the Farm Model and Management Strategies, Soil Data Analysis and Modelling

The second phase of this study, which addressed the data collection part of the specific objective 3, was when I conducted a field experiment from December 2017 to April 2018 in northern Togo. The field experiment consisted in using the irrigation schedules produced in the initial phase (Figure 2) to assess the effects of full and deficit irrigation on maize production in the study area. During the field experiments, soil samples were taken and examined in the laboratory. The ku-pF apparatus DT 04-01 was used to measure soil water retention (Schindler, 1980) (Figure 3a). The permeameter was used to measure the soil saturated hydraulic conductivity (Figure 3b). The Pario apparatus (Figure 3c) was utilised to measure the soil particle size analysis following the German standard DIN ISO 11277 2002-08 (DIN, 2002). The integral suspension pressure method (ISP) (Durner, Iden and von Unold, 2017) was used to analyse the particle size distribution. The electrical conductivity meter (Figure 3d) was used to measure the soil electrical conductivity following the German standard DIN ISO 11265:1997-06 (DIN, 1997).

Figure 3. Soil laboratory measurements with (a) Ku-pF apparatus, (b) permeameter, (c) Pario apparatus, and (d) Electrical Conductivity meter

Maize crop growth parameters such as the above-ground biomass, the canopy cover, the leaf area index, the plant height, and the grain yield were measured during the field trial. The appearance of the maize fields during the initial (Figure 4a), development (Figure 4b), mid-season (Figure 4c), and late-season (Figure 4d) growth stages is shown in Figure 4. This phase of the workflow was described in detail in the second research paper of this study.

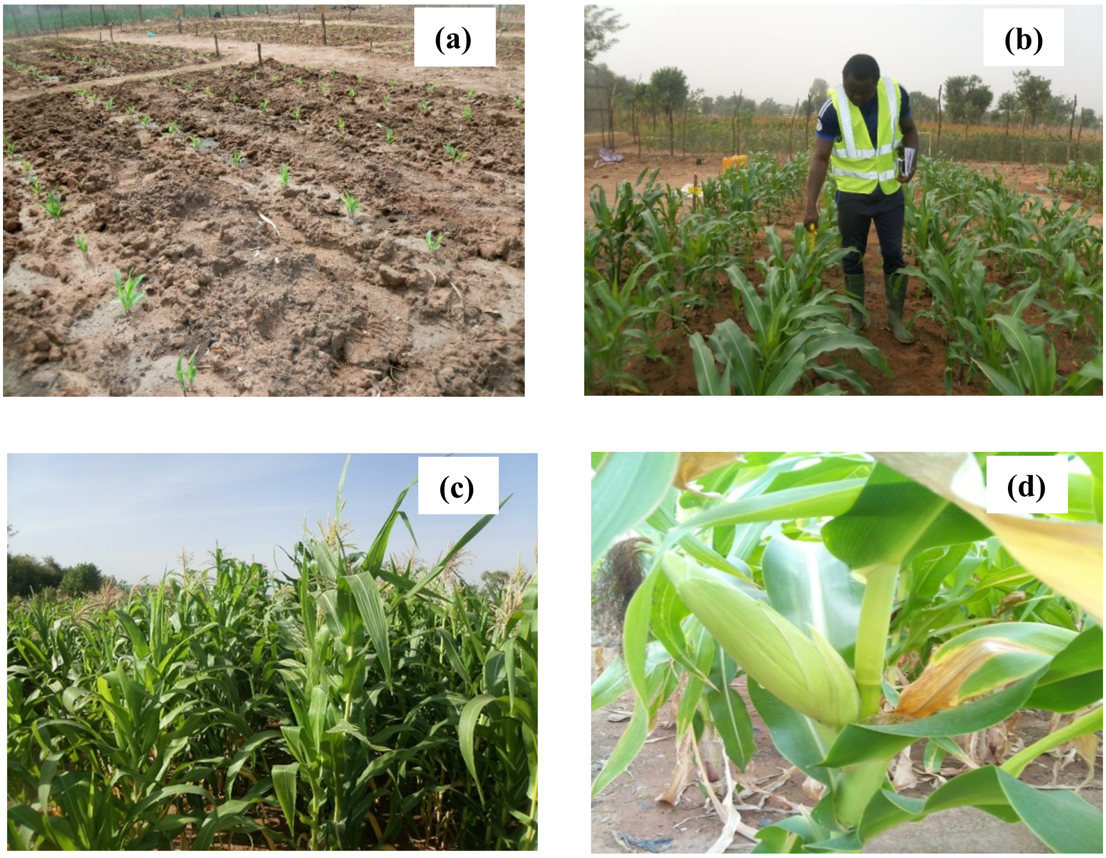

Figure 4. Field experiment: maize crop growth stages (a) initial, (b) development, (c) mid-season, and (d) late-season

3.3 Joint Stochastic Analysis of the Impact of Climate and Soil Variability on Crop Water Productivity and Food Security

In the phase final of this study (Figure 5), similar steps to the initial phase were undertaken. This phase of the workflow addressed the specific objective 3 of the study. The authors of this study directly measured, this time, the crop and soil data. These data served for the validation of the results obtained from the initial phase and for the calibration of the AquaCrop model, which is the maize yield predictor included in the modified OCCASION framework. Unlike the initial phase, this time, a random soil texture generator was developed and applied to generate a large number of synthetic basic soil data from the laboratory-measured texture data or a soil textural class. This allowed me to assess the maize yield response to soil variability in the study area. As outputs, the stochastic crop water production functions were derived from the simulations. Details of this phase of the workflow were provided in the third research paper of this study.

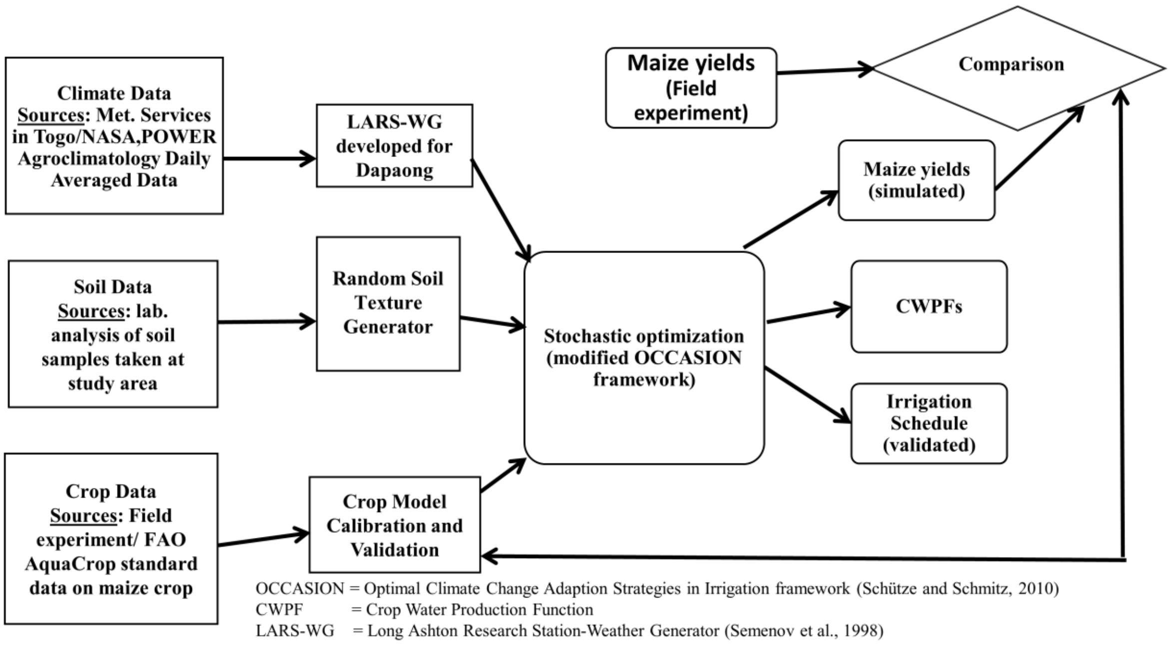

Figure 5. Final phase: after the field experiment

4. Overview of Publications

4.1 Potential of Deficit and Supplemental Irrigation under Climate Variability in Northern Togo, West Africa

This paper investigated the impact of climate variability on maize yield in northern Togo by assessing different irrigation management strategies, including rainfed conditions. Observed climate data obtained from the Togolese national meteorological station, crop growth and yield, and soil data retrieved from previous studies in the area were used for the assessment. This article addressed the specific objectives 1 and 2 of the PhD research work.

In the context of an increasing population in West Africa and frequent yield losses due to erratic rainfall and recurrent meteorological and agricultural droughts, it is essential to improve agricultural productivity, e.g., by evaluating and introducing irrigation management strategies, which may be implemented in this region. Thus, T1: no irrigation (NI), T2: controlled deficit irrigation (CDI) and T3: full irrigation (FI) in wet season and T4: controlled deficit irrigation (CDI) and T5: full irrigation (FI) in dry season were evaluated regarding their impact on the inter-seasonal variability of the expected yields. This modelling study was carried out on maize (*Zea mays* L.) at a field level in northern Togo.

This study adapted and utilised the OCCASION framework. It comprises: (i) a weather generator for predicting long-term climate time series data; (ii) the AquaCrop model, which was used to predict the irrigation system during the growing period and the yield response of maize to a given irrigation management strategy; and (iii) a problem-specific algorithm for ideal irrigation scheduling with limited water supply. High variability was found in rainfall during the wet season, leading to substantial variability in the expected yield under rainfed conditions (NI). The application of supplemental irrigation management strategies (CDI or FI) led to a significant reduction in the yield variability. Both irrigation management strategies (CDI and FI) led to an increase in the yield potential for the local variety TZEE-W up to 4,840 kg ha^{-1} and a decrease in the variability of the expected yield at the same time in the dry season. However, more than 400 mm of water is needed to introduce irrigation during the dry season under the CDI management in northern Togo.

In a nutshell, the main findings of this paper are:

- Significant variability was observed in the expected yields under rainfed conditions;
- This variability was significantly reduced when supplemental irrigation was applied;

- In the dry season, the irrigation management strategies assessed would increase yield potential and decrease the variability of the expected yields at the same time.

In conclusion, there is a need for substantial rainwater harvesting and irrigation infrastructures to introduce irrigation in the dry season.

This investigation focused only on climate variability—temperature, rainfall, carbon dioxide concentration, and global radiation. However, other yield-limiting factors such as soil variability which could have been included in the simulation framework were not considered due to lack of laboratory analysis soil data. In this study, the conclusions derived from the outputs of the model simulation should be viewed qualitatively because the AquaCrop model was calibrated with crop and soil data retrieved from previous studies conducted in the study the area. Thus, there is a room for conducting field experiments to recalibrate the crop model and collect and analyse soil samples to assess the soil variability impact on maize yield.

4.2 Impact of Irrigation Strategies on Maize (*Zea mays L.*) Production in the Savannah Region of Northern Togo (West Africa)

This article explored the impact of different irrigation management strategies on maize growth parameters and yield. This was done through a field experiment conducted in the savannah region of northern Togo. The irrigation schedules applied in this field experiment were generated from the adapted OCCASION framework with preliminary calibrated AquaCrop model described in the first research paper. This paper addressed the data collection part of the specific objective 3 of the PhD research work.

Rainfed maize is one of the major crops grown in the dry savannah of northern Togo. Farmers are experiencing low crop yields because of the erratic rainfall and low soil fertility. Producing maize during the dry season through irrigation is necessary to improve agricultural productivity and ensure food availability. A sound application of full and limited irrigation requires a thorough understanding of the crop parameters and yield response to water. Thus, this study investigated the effect of full and deficit irrigation on maize (*Zea mays L.*) canopy cover, plant height, leaf area index, above-ground biomass, and grain yield.

From December 2017 to April 2018 a field experiment was carried out in Dapaong area in northern Togo at ITRA research station. The full irrigation (FI), 80% FI and 60% FI irrigation treatments were evaluated. The results revealed that in the late-season stage, there were significant ($p < 0.05$) differences in the above-ground biomass between the FI and 60% FI. On average, the greatest grain yield (2,200.4 kg ha^{-1}) was recorded in the fully irrigated treatment, while the lowest grain yield was recorded under the 60% FI (1,068.3 kg ha^{-1}). There were significant ($p < 0.05$) differences between FI and 60% FI grain yield. Nevertheless, there were non-significant ($p > 0.05$) differences between FI and 80% FI grain yield. The 80% FI had water productivity (0.22 kg m^{-3}) similar to that of fully irrigated treatment (0.21 kg m^{-3}) on average. This holds for the outputs of simulating the experiment with the AquaCrop model. Under a moderate level of deficit irrigation during the vegetative and reproductive growth stages, the above-ground biomass and the grain yield of maize are reduced. Nevertheless, a moderate level of deficit irrigation during the vegetative growth stage only may lead to similar values of water productivity to that of fully irrigated treatment under these experimental, soil and crop management, and climatic conditions.

The most striking finding of this paper is that a moderate level of deficit irrigation could lead to a reduction in maize above-ground biomass and the grain yield. In conclusion, the findings of this investigation illustrate that deficit irrigation strategies must be carefully managed since slight differences in the application volumes affect the above-ground biomass and grain yield of maize significantly.

This investigation gives substantial insights into maize crop response to irrigation regimes because to date, no work has been published on similar topics in northern Togo. However, the soil variability dimension was missing in the evaluation. Thus, the framework used to simulate the irrigation schedules can be extended by adding a soil variability dimension to it. The maize crop growth data, as well as the soil data collected during the field experiment, can be utilised to recalibrate the AquaCrop model and include the soil variability dimension to the simulation framework.

4.3 Impact of climate and soil variability on maize (*Zea mays L.*) yield under full and deficit irrigation in the savannah region of northern Togo, West Africa

This paper dealt with the impact of climate and soil variability on maize yield assessing full and deficit irrigation in the savannah region of northern Togo. It used the outputs and data generated in the first two papers of this study. This article addressed the specific objective 3 of the PhD research work.

In the situation of an increasing population in West Africa, frequent yield losses due to erratic rainfall, and degraded soils, the knowledge of the impact of climate and soil variability on maize (*Zea mays L.*) yield is needed to improve maize production in the region for long-term. Thus, full irrigation and controlled deficit irrigation management strategies under different soil and climate variability scenarios were investigated in this study. The impact of soil variability on maize yield was assessed by developing and applying a stochastic soil generator. Rosetta 3 and Saxton and Rawls pedotransfer functions were utilised to convert the synthetic basic soil data into hydraulic characteristics which served as inputs to the crop model. A field experiment was conducted on maize from December 2017 to April 2018 to validate the AquaCrop preliminary calibration for the study area. Also, the OCCASION which considers climate variability was adapted and applied. Overall, based on the values of the statistical indicators, AquaCrop simulated well the canopy cover, above-ground biomass, and grain yield for all the irrigation treatments assessed. It was found that the maximum expected maize yield ranged from 2,500 to 3,000 kg ha^{-1} considering all the scenarios investigated in this study. The full irrigation storage was reached between 350 mm and 500 mm when all scenarios assessed were considered. Also, the results of this study showed that climate variability might lead to higher variability in the maize yields of northern Togo than soil variability does. The findings of this study indicate that the AquaCrop model could be used to simulate the maize yield with acceptable accuracy under different irrigation management strategies in data-scarce regions like West Africa.

The most striking findings from this paper are as follows:

- AquaCrop has simulated accurately the canopy cover, above-ground biomass, and grain yield for all the irrigation strategies evaluated;
- Climate variability might lead to higher variability in the maize yields of northern Togo than soil variability does.

In conclusion, large- and small-scale water harvesting, access to groundwater, and irrigation infrastructures would be needed to implement the irrigation management strategies assessed in this study.

This study brings substantial contributions to understanding maize crop response to the deficit and full irrigation strategies in northern Togo. This investigation has concluded that the AquaCrop model can be used to predict maize yield in northern Togo based on the results of its calibration with the measured data collected during the field experiment carried out in the area. Also, the soil variability dimension was considered in the analysis in addition to that of the climate. This investigation may be reproduced at other sites in the West African region in order to establish a regional water management strategy for food security enhancement. However, establishing such a strategy will require considering farmers' social, demographic, and economic traits for a comprehensive assessment.

From this chapter, it should be borne in mind that the first paper contributed to achieving the specific objectives 1 and 2 of this study, while the second and third papers made the specific objective 3. There were direct linkages between the three research papers that emanated from this study. The optimised irrigation schedules produced in the first paper were used to carry out the field experiment, which was the backbone of the second paper. Then, the data collected through the second paper were used for calibration and simulations in the third paper. Overall, the findings of this study can be summarised as follows:

- Significant variability was observed in the expected yields under rainfed conditions;
- This variability was significantly reduced when supplemental irrigation was applied;
- In the dry season, the irrigation management strategies assessed would increase yield potential and decrease the variability of the expected yields at the same time;
- A moderate level of deficit irrigation could lead to a reduction in maize above-ground biomass and the grain yield;
- AquaCrop has simulated accurately the canopy cover, above-ground biomass, and grain yield for all the irrigation strategies evaluated;
- Climate variability might lead to higher variability in the maize yields of northern Togo than soil variability does.

Large- and small-scale water harvesting, access to groundwater, and irrigation infrastructures would be needed to implement the irrigation management strategies assessed in this study. However, putting in place such a strategy will demand considering farmers' socioeconomic and demographic characteristics for a comprehensive evaluation.

5. Conclusion and Outlook

In West Africa, climate variability and soil fertility depletion are critical drivers of year-to-year impact on crop yield. The low crop productivity of smallholder farmers in West Africa may be attributed to the lack of good quality of water and soil resources. These crop yield-limiting factors have more influence on the agricultural production systems in the semi-arid areas of West Africa, such as northern Togo. To properly understand their impact on the agricultural system in northern Togo, it is necessary (i) to assess the response of the crops to climatic parameters, especially to water, (ii) to evaluate the potential of deficit and supplemental irrigation, and (iii) to quantify the impact of climate and soil variability on maize, which is a staple food in northern Togo.

This study lays a foundation for the appraisal of crops response to climate and soil variability in Togo. It brings substantial insights to understanding maize crop response to the deficit and full irrigation strategies in northern Togo. The irrigation management strategies investigated in this study would increase yield potential and decrease the variability of the expected yields at the same time. This implies that, scientifically, introducing irrigation in northern Togo is an option to enhance food security in the area. The AquaCrop model has simulated accurately the canopy cover, above-ground biomass, and grain yield for all the irrigation strategies evaluated. This indicates that AquaCrop could be used for maize yield forecasting in northern Togo to reduce yield variability and losses and strengthen food security. Climate variability might lead to higher variability in the maize yields of northern Togo than soil variability does. This implies that more focus should be given to climate variability when implementing projects related to improving crop productivity in northern Togo.

To ensure food security—by establishing a regional water management strategy—this study may be reproduced at other locations in the West Africa region. For this, there will be a need to consider farmers' socioeconomic and demographic characteristics for a comprehensive assessment. Thus, an economic-based evaluation of irrigation water can be carried out in order to quantify water productivity and farmers' profit in the study area. In the present study, LARS-Weather Generator was used to generate long-term time-series climate data from observed data. Further studies should be carried out to downscale and bias-correct the outputs of Regional Climate Model (RCM) and General Circulation Model (GCM) in order to give broader applicability to the present study. These data may be used to assess climate variability impact on crop yield by applying the framework developed in this study to West Africa as a region. Open-loop will permit to consider an ensemble of climate models for a better assessment of the climate variability impact on crop yield because of the uncertainties that lie in the outputs of the RCM and GCM. Further studies are needed to fine-tune maize crop genetic (seeds) to the dry season climate conditions in order to have better heat-tolerant crops. This may be achieved through the crop seeds improvement programme, which is being implemented in the five regions of Togo under the expertise of the ITRA. There is also a room for including other robust crop models such as DSSAT and APSIM in the framework developed in this study for its broader applications.

Given the current debate on risk-sharing in the agricultural sector in Togo and the ongoing pilot program of the Ministry of Agriculture on climatic risk-sharing entitled “Mechanism for Promoting Agricultural Financing (MIFA)”, there is a need to reproduce the present study in all the agroecological zones of Togo. This will help to strengthen the scientific basis of MIFA program by categorising all the agroecological zones regarding the climatic risk in the agricultural production systems in Togo. For this, the primary cereals (maize, sorghum, fonio, and millet) and vegetables (onion, tomato, lettuce, and chilli pepper) crops consumed in Togo should be considered in the agroecological zones assessment. The Togolese Institute of Technical Support Council for Agriculture (ICAT) may help to do this through its programme on lowland development, good agroecological practices in rural areas at small and large scales, construction and improvement of reservoirs for micro-irrigation and livestock watering in rural areas in Togo. It should be noted that implementing supplemental irrigation in the wet season in northern Togo would be a good start since it requires less investment than deficit irrigation in the dry season.

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A. Selected Publications of the Author

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Gadédjisso-Tossou, A., Avellán, T., Schütze, N.

Potential of Deficit and Supplemental Irrigation under Climate Variability in Northern Togo, West Africa.

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Gadédjisso-Tossou, A., Avellán, T., Schütze, N.

Impact of Irrigation Strategies on Maize (*Zea mays L.*) Production in the Savannah Region of Northern Togo (West Africa).

Water SA 2019, Accepted for publication

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Gadédjisso-Tossou, A., Avellán, T., Schütze, N.

Impact of climate and soil variability on maize (*Zea mays L.*) yield under full and deficit irrigation in the savannah region of northern Togo, West Africa.

In preparation for submission

water

Water 2018, 10, 1803; doi:10.3390/w10121803

MDPI

A.1 Potential of Deficit and Supplemental Irrigation under Climate Variability in Northern Togo, West Africa

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Received: date; Accepted: date; Published: date

Abstract: In the context of a growing population in West Africa and frequent yield losses due to erratic rainfall, it is necessary to improve stability and productivity of agricultural production systems, e.g., by introducing and assessing the potential of alternative irrigation strategies which may be applicable in this region. For this purpose, five irrigation management strategies, ranging from no irrigation (NI) to controlled deficit irrigation (CDI) and full irrigation (FI), were evaluated concerning their impact on the inter-seasonal variability of the expected yields and improvements of the yield potential. The study was conducted on a maize crop (*Zea mays* L.) at a representative site in northern Togo with a hot semi-arid climate and pronounced dry and wet rainfall seasons. The OCCASION (Optimal Climate Change Adaption Strategies in Irrigation) framework was adapted and applied. It consists of: (i) a weather generator for simulating long climate time series; (ii) the AquaCrop model, which was used to simulate the irrigation system during the growing season and the yield response of maize to the considered irrigation management strategies; and (iii) a problem-specific algorithm for optimal irrigation scheduling with limited water supply. We found high variability in rainfall during the wet season which leads to considerable variability in the expected yield for rainfed conditions (NI). This variability was significantly reduced when supplemental irrigation management strategies (CDI or FI) requiring a reasonably low water demand of about 150 mm were introduced. For the dry season, it was shown that both irrigation management strategies (CDI and FI) would increase yield potential for the local variety TZEE-W up to 4.84 Mg/ha and decrease the variability of the expected yield at the same time. However, even with CDI management, more than 400 mm of water is required if irrigation would be introduced during the dry season in northern Togo. Substantial rainwater harvesting and irrigation infrastructures would be needed to achieve that.

Keywords: Aquacrop model; maize; deficit irrigation; crop-water production function; West Africa

1. Introduction

The present world population of 7.3 billion will increase to 9.7 billion by 2050 [1]. Similarly, the medium variant of the UN Population Division [2] predictions disclose that the total population of the West African region would increase from 350 million in 2015 to 450 million in 2030, and nearly 800 million in 2050. FAO [3] estimates that agricultural production will have to rise by 60% by 2050 to meet the world's projected demands for food and feed. In West Africa, Liniger et al. [4] reported that food production should increase by 70% by 2050 to meet the necessary caloric requirements. However, a lack of available water for agricultural production, the energy sector, and other forms of anthropogenic water consumption is already harming several parts of the world. This lack of water is projected to become more severe with the growing population, rising temperatures, and altering precipitation patterns [5]. The variation of the food diets in many developing countries compound

This problem and lead to the demand for more processed food and animal proteins by consumers [6].

The World Bank [7] reports that the rate of increase in food demand is projected to be higher in developing than in developed countries. These are also the regions that are subject to a wide yield gap. The world demand (billion tons) of cereals was 1.20 in 1974, 1.84 in 1997 and is expected to be 2.50 in 2020 [8]. In addition, van Ittersum et al. [9] pointed out that Sub-Saharan Africa (SSA) is the region with lowest food security because by 2050 its demand for cereals will almost triple, whereas current levels of cereal consumption already rely on considerable importations.

Lobell and Gourdji [10] pointed out that, in the past several decades, air temperatures have been increasing in most of the main cereal cropping areas around the world. They added that the changes in temperature and the intensity and seasonal volume of rainfall are impacting soil moisture. In turn, soil moisture is of high importance for crop production. In developing countries, particularly, the changes in these climatic variables over time are likely to have a damaging impact on water accessibility, which in turn affects crop yield. Kotir [11] and Druyan [12] stressed the fact that researchers have described Sub-Saharan Africa as the most sensitive region to the impacts of climate variabilities and change because of its dependence on rainfed agriculture and low capacity for adaptation. Moreover, Sarr [13] contended that the West African region had faced decades of severe drought, which have affected agricultural production substantially. The observations already show the late onset and early cessation dates of rainfall and the reduction of length of the growing period.

According to the Togolese Ministry of the Environment and Forestry (MERF) [14], in the dry savannah of northern Togo, a West African country, the wet season, which spanned six months in the 1970s, was reduced to five or four months nowadays. Consequently, on the one hand, a substantial amount of rainwater falls within a short period causing flooding, while, on the other hand, frequent dry spells in the wet season lead to crop failure [15]. In addition, there is no rainfed agricultural activity during the dry season in northern Togo because of a lack of rainfall [16].

Researchers and practitioners are putting more focus on producing more with limited resources in agriculture to meet the food demand and at the same time address the adverse effects of climate change [17–19]. Agriculture, which accounts for 38% of Togo's gross domestic product, provides over 20% of export earnings and employs 70% of the active population. Togolese agriculture is predominantly rainfed [20,21]. According to the International Commission on Irrigation and Drainage (ICID) [22], rainfed agriculture is "agriculture without application of irrigation. It may be without, or with a drainage system." A promising practice to overcome water shortage in rainfed cropping systems is supplemental irrigation (SI). The ICID [22] defines SI as: "the addition of small amounts of water to essentially rainfed crops during times when rainfall fails to provide sufficient moisture for normal plant growth, in order to improve and stabilize yields." SI practice increases yields and water productivity in rainfed cropping systems [23]. In addition, conventional irrigation systems can be used to improve crop productivity. The ICID [22] defines conventional irrigation as: "the replenishment of soil water storage in the plant root zone through methods other than natural precipitation".

Irrigation scheduling is the procedure of deciding when, where, and how much water to apply [24] for irrigation. Farmers can apply the total crop-water requirements or more in the right period if water is available. This practice is called full irrigation (FI). When water provisions are limited, or irrigation expenses are great, FI may be substituted by deficit irrigation (DI) [25]. This is limited irrigation scheduling in agriculture [26]. DI can be controlled or otherwise. Uncontrolled DI is equivalent to rainfed agriculture. English [27] and English and Raja [28] defined controlled deficit irrigation (CDI) as the concept of intentionally and systematically under-irrigating a crop. English [27] developed an analytical framework to evaluate the profit when optimizing water use. Thus, he included implicitly economic aspects in the definition. Later, Lecler [29] provided a more explicit definition: "CDI is an optimization strategy by which net returns are maximized by lessening the volume of irrigation water applied to a crop to a level that results in some yield loss caused by water stress". Recently, Fereres and Soriano [30] defined CDI as the application of water below full crop-water requirements or evapotranspiration. The objective of applying limited water is to cope with scarce water supplies and improve productivity. Kögler and Söffker [31] reported that CDI practice contributes to saving up to 20–40% irrigation water at yield reductions under 10%. It can contribute to increasing farmers' net income where water is scarce [27]. Thus, CDI is an irrigation management practice that contributes to enhancing food security.

Many studies that applied the simulation-based approach to assess deficit irrigation strategies failed to consider the variability of relevant climate factors—such as precipitation and temperature—and soil properties [32,33]. Semenov [34] and Brumbelow and Georgakakos [35], among others, analyzed possible impacts of climate variability and climate change on agriculture using process-based simulation models. Most of these studies only look at rainfed or non-irrigated sites or assumed full irrigation. Few researchers, including Schütze and Schmitz [36] and Brumbelow and Georgakakos [35], assessed limited irrigation systems and the impact of climate variability on crop-water production functions (CWPF). Brumbelow and Georgakakos [35] derived probability distribution functions of CWPF (CWPF-PDs) using climate change scenarios data of the Intergovernmental Panel on Climate Change (IPCC). Schütze and Schmitz [36] delved into the CWPF concept and suggested a stochastic framework in the form of a decision support tool for Optimal Climate Change Adaption Strategies in Irrigation (OCCASION) for deriving site-specific stochastic CWPFs (SCWPFs). To perform such analyses, one needs to utilize crop models to simulate the potential or expected crop yield for a given soil, climate, and management practice condition.

Several crop simulation models such as DSSAT [37], AquaCrop [38–40], DAISY [41], CropWat [42], APSIM [43], and PILOTE [44] are available in the literature to simulate yield response to water. It is important to recognize that most of these models show substantial complexities and require several data to run. Most of these models require many parameters to run, and many are not readily available in the field and need to be determined experimentally [45]. Exceptionally, the AquaCrop model uses relatively few explicit and mostly intuitive parameters and input variables, requiring simple methods for their derivation [46]. For instance, unlike AquaCrop, the DSSAT model requires input data about crop genetics and pest management [37], while APSIM requires NO_3 and NH_4 content of the soil layers [43].

Few studies have investigated irrigation management strategies on crops in the dry savannah area of northern Togo [20]. Therefore, this study assessed the potential of deficit and supplemental irrigation in northern Togo. Specifically, the study aimed at: (i) characterizing the climate of a water-scarce site in northern Togo, West African region; and (ii) evaluating five irrigation management strategies, ranging from no irrigation (NI) to CDI and FI for a maize crop (*Zea mays L.*) at a representative site in northern Togo with pronounced dry and wet rainfall seasons.

2. Materials and Methods

2.1. Study Area

Togo is a small West African francophone country. It is bordered by the Bight of Benin and Burkina Faso in the south and north, respectively. Togo is bound in the west by Ghana and in the east by Benin. Geographically, it lies between latitudes 6°N and 11°N, and longitudes 0°E and 2°E. It covers a surface of 56,600 km^2 and has a long, narrow profile, stretching more than 550 km from north to south but not exceeding 160 km in width [47]. Its population is estimated to be 6,191,155 [48].

We conducted this study in the Dapaong district, northern Togo (Figure 1). Dapaong belongs to the Southern-Guinea-Savannah agro-ecological zone [49]. The principal rainfed crops grown include maize (*Zea mays*), sorghum (*Sorghum bicolor*), and pearl millet (*Pennisetum glaucum*), mainly for subsistence, while cash crops such as cotton (*Gossypium hirsutum*) are also cultivated. Some vegetables and legumes such as okra (*Abelmoschus esculentus*), cowpea (*Vigna unguiculata*), and soybean (*Glycine max*) are grown in association with the cereals mentioned above. The vegetation type is a woody savannah, with noticeable agricultural farms. The primary tree species are *Parkia biglobosa*, *Butyrospermum parkii*, and *Acacia sieberiana* [50]. The Togolese Institute of Agricultural Research

(ITRA) [51] and Didjeira et al. [52] identified maize crop as the staple food in Togo, and it represents 60% of the cereals consumed by the population. On the farms close to the houses, the main cropping system is intercropping (cereal–legume mixtures), while on the farms far from the houses, farmers practice monoculture [53]. Since cotton is grown with a high level of pesticides, intercropping is not possible on cotton farms. Hoes and cutlasses are the primary tools of cultivation.

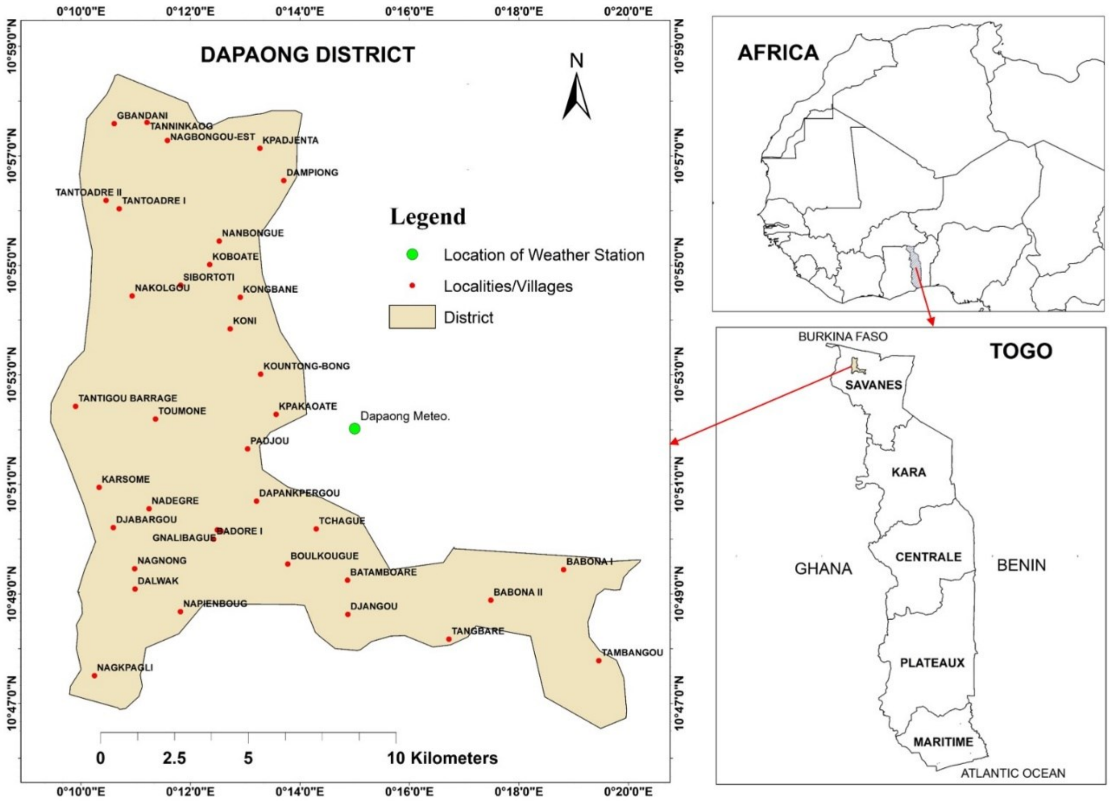

Figure 1. Map of northern Togo indicating the study area (Dapaong district).

According to Köppen–Geiger's climatic classification, the climate of Dapaong district is hot semi-arid (BSh) [54]. The period from mid-April to mid-October is humid, while in the other months dry conditions predominate in Dapaong. The months from June to September show high rainfall (Figure 2). These high annual values of rainfall are sufficient for rainfed cereal crops in northern Togo. The annual rainfall is, however, very unequally dispersed. From November to March (or sometimes April), there is practically no rainfall in the area. From May to October, a substantial amount of rainfall is recorded. Consequently, northern Togo is characterized by a single wet season in a year. This explains why farmers adopt intercropping to obtain the range of crops they need. Introducing irrigated crops in the dry season may help farmers to sustain their production. The mean annual temperature is 28.1 °C, and the annual total precipitation is 1050 mm. The mean daily maximum temperature of the driest month is around 37 °C, whereas the mean daily minimum temperature of the wettest month is 20 °C (Figure 2). In January and February, a robust dusty wind named harmattan, blowing in the northeast direction from the Sahara Desert, increases the dryness of the weather in the area [16].

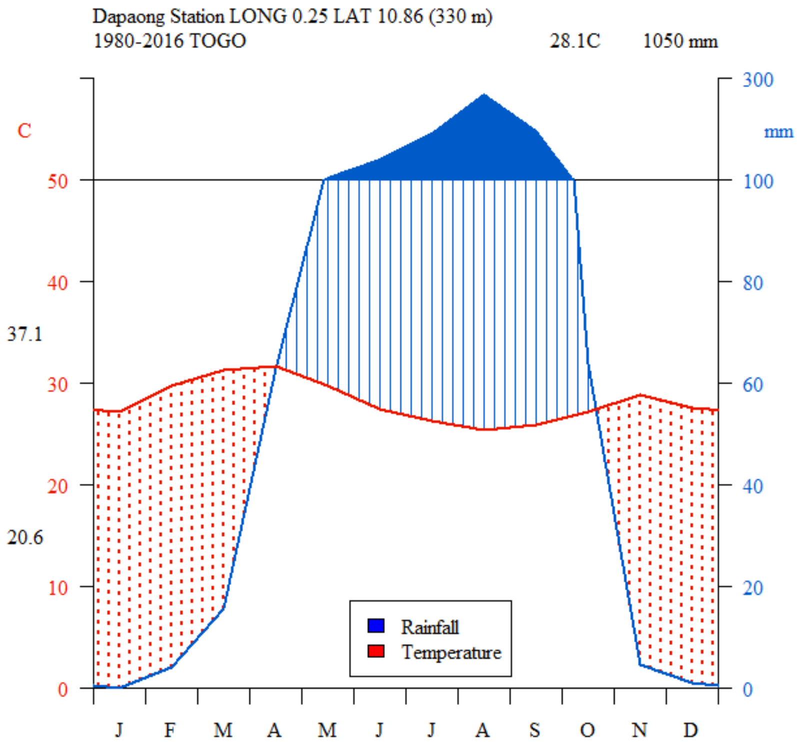

Figure 2. Walter–Lieth [55] climate diagram for northern Togo based on data collected at Dapaong Meteorological Station (Latitude: 10°51′44.10″ N, Longitude: 0°12′27.43″ E, Altitude: 330 m above sea level). Rainfall and temperature data were measured between 1980 and 2016.

With a population density of 96 inhabitants per km^2, over 88% of the population live under the poverty line (US$ 2/day) [56,57]. Complicated communal land tenure favors men and encourages farm fragmentation. Women access only marginal lands characterized by reduced soil fertility. Most farmers are smallholders with less than 1.5 ha of land under cultivation [53]. Crop yields are generally low due to erratic rainfall, low soil fertility, low-quality seeds, and inappropriate land preparation tools, among others. Farmers' livelihood depends on small-scale farms with low input, and mixed crop–livestock agriculture. Regarding poultry, most farmers have local hens, cocks, and guinea fowls in their houses. Some families raise local dwarf goats and pigs [53].

2.2. Methods

2.2.1. Adapted Framework for the Evaluation of Irrigation Management Alternatives

In this study, we investigated five irrigation management strategies. These are NI, CDI for supplemental irrigation, CDI for conventional irrigation, FI for supplemental irrigation, and FI for conventional irrigation. The NI is equivalent to the rainfed system; the type of agriculture most farmers are practicing in Dapaong. When rainfall is unevenly distributed throughout the wet season, farmers have the option to apply an optimal amount of irrigation water to supplement the shortage (CDI for SI) or use the fully required amount (FI for SI). On the other hand, in the dry season, farmers can deliberately apply an optimal amount of irrigation water (CDI for conventional irrigation) or fully irrigate the plants (FI for conventional irrigation). When combining these strategies with dry and wet seasons, we obtain the following: (i) NI for the wet season (WS-NI); (ii) CDI for supplemental irrigation system in the wet season (WS-CDI); (iii) full irrigation for supplemental irrigation system in the wet season (WS-FI); (iv) CDI for conventional irrigation system in the dry season (DS-CDI); and (v) full irrigation for conventional irrigation system in the dry season (DS-FI). In this study, one should bear in mind that we only dealt with the physiological and agronomical aspects of DI—crop response to different irrigation regimes—without any economic evaluation. The summary can be seen in Table 1.

Table 1. Irrigation management strategies investigated.

Type of Irrigation System	Irrigation Management Strategies			Application Scenarios	
	Limited Supply		Full Supply		
	Uncontrolled	Controlled	Controlled	Wet Season (WS)	Dry Season (DS)
No irrigation	NI	–	–	x	–
Supplemental irrigation	–	CDI	FI	x	–
Conventional irrigation	–	CDI	FI	–	x

CDI, controlled deficit irrigation; FI, full irrigation; NI, no irrigation.

The OCCASION framework was adapted and used to assess the five irrigation management strategies mentioned above (Figure 3). The adapted framework consists of: (i) a weather generator for simulating long climate time series; (ii) the AquaCrop model, which was used to simulate the irrigation system during the growing season and the yield response of maize to the considered irrigation management strategies (Figure 3, Loop 1); and (iii) a problem-specific algorithm for optimal irrigation scheduling with limited water supply (Figure 3, Loop 2). The latter is named Global Evolutionary Technique for OPTimal Irrigation Scheduling (GET-OPTIS) (For more details, see [33]). A range of given maximum volumes of water is then assigned; a complete CWPF can be derived. The produced CWPF characterizes the maximum yields that can be attained with a given amount of water and is designated the potential CWPF. Then, the crop simulation model was run for a long-term climate time series data yielding a necessary amount of CWPFs. Also, optimized irrigation schedules are obtained. Subsequently, the resulting CWPFs were analyzed, and the SCWPFs obtained through parameters of descriptive statistics such as mean, median, and the probability of exceedance, among others. SCWPFs are empirical probability functions where, for every volume of applied irrigation water, the marginal distribution function of the yield related to it can be derived. The probability of exceedance represents the reliability that a specific yield can be achieved [32].

2.2.2. Processing of Climate Data and Set-Up of the LARS Weather Generator

Historical weather observations, including daily maximum temperature, daily minimum temperature, daily rainfall, daily wind speed, daily minimum humidity, and daily maximum humidity were obtained from the nearest meteorological station to the study site—courtesy of the National Weather Service of Togo. These daily weather data available at the station range from 1983 to 2011. In addition, the observed monthly rainfall and maximum and minimum temperatures data from 1980 to 2016 were provided. These monthly data were utilized to characterize the climate of northern Togo with the climate diagram of Walter and Lieth [55]. The Dapaong meteorological station is located at latitude 10°51′44.10″ N, longitude 0°12′27.43″ E, and altitude 330 m above sea level (Figure 1). The solar radiation data, as well as sunshine hours data, were not available at Dapaong weather station. As a substitute, the uncorrected gridded incident solar radiation from the Prediction of Worldwide Energy Resource dataset from the National Aeronautics and Space Administration project NASA-POWER [58] was utilized. Van Wart et al. [59] showed that NASA-POWER is a good source of climate data for crop yields simulation studies. It is publicly accessible, shows acceptable general agreement with ground data for incident solar radiation, and has been used by similar previous studies (See section 2.2.4).

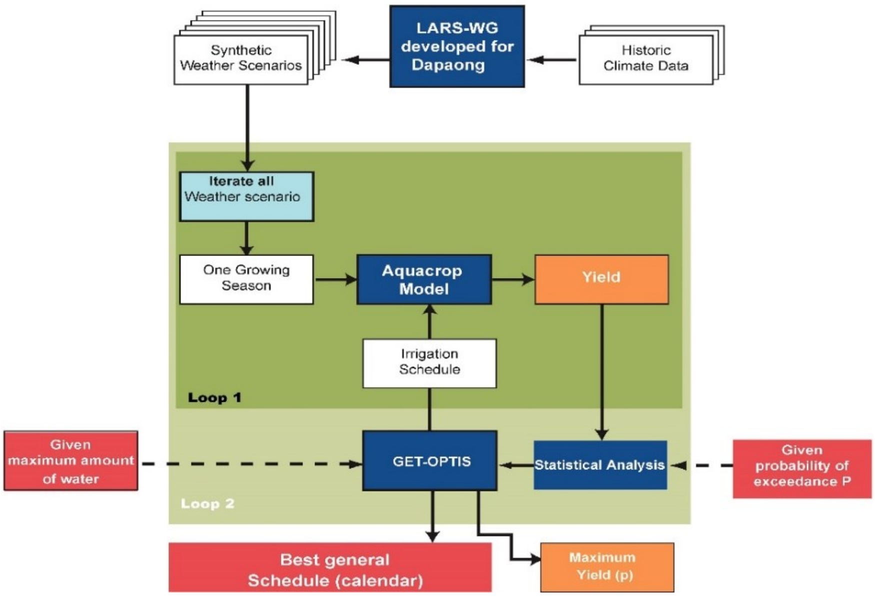

Figure 3. General framework for generating stochastic crop water production functions (adapted from Schütze and Schmitz [36]).

Since the 29-year period (1983–2011) of weather data is not long enough to be used in the assessment of climate variability effect on crop yield, the Long Ashton Research Station Weather Generator version 4.0 (LARS-WG)—a stochastic weather generator—was used to generate a 100-year period of near future climate data. In this study, out of the existing weather generators, LARS-WG was used for two reasons. Firstly, it uses more complex distributions for weather variables and has been tested for diverse climates and found to be better than some other weather generators such as WGEN [60] (Appendix A). Secondly, Semenov [61] recently tested LARS-WG at different locations across the world and revealed its ability to model rainfall extremes with acceptable performance. Similarly, Mehan et al. [62] provided insights into the suitability of LARS-WG for use with water resource applications. Guo et al. [63] suggested performing more than a single realization when generating weather data using LARS-WG for hydrologic and environmental applications. We assessed the performance of the LARS-WG in simulating weather data of Dapaong by comparing the observed and the simulated data with the Kolmogorov–Smirnov test (KS-test). We used the KS-test for the comparison of the probability distributions for each month. The KS-test is a non-parametric and distribution-free test that tries to determine if two datasets are extensively different and come from different distributions. It is an alternative to the Chi-square goodness of fit test. The KS-test compares the two empirical distribution functions as in Equation (1) [64].

$$D = \left|E_1(i) - E_2(i)\right| \quad (1)$$

where E_1 and E_2 represent the empirical distribution functions of the two distributions, and D is the absolute difference between them.

The KS-test examines changes in distributions coming from the generated and observed weather. The KS-test calculates a test statistic and an equivalent *p*-value [65]. It shows how likely it is that the generated and observed data originate from the same distribution. If the *p*-value is very low and below the significance level, set to 0.01 or 0.05, the simulated climate is unlikely to be the same as the "true" climate. Although a *p*-value of 0.05 is the standard significance level employed in most statistics, the authors of the LARS-WG model recommended that a *p*-value of 0.01 should be considered as the satisfactory significance level.

The calibrated LARS-WG for Dapaong was then used to forecast the 100-year daily rainfall and temperature data mentioned above for the near future. For this, the outputs of the General Circulation

Models (GCMs) HADCM3 (Hadley Centre Coupled Model version 3) of the IPCC Special Report on Emission Scenarios (SRES) A2 were inputted into LARS-WG. The HADCM3 is the product of the UK Meteorological Office, gridded as 2.5° × 3.75°. These long-term data were used to run the AquaCrop model to assess the five irrigation management strategies.

2.2.3. Description and Set-Up of the Crop Simulation Model

AquaCrop, a water-driven crop simulation model, was developed in 2009 by the Food and Agriculture Organization (FAO) of the United Nations [38–40]. The development of the AquaCrop model is based on the algorithm of yield response to water in FAO Irrigation and Drainage Paper No. 33 [66]. AquaCrop evolves from the previous Doorenbos and Kassam [66] Ky approach (Equation (2)), where relative evapotranspiration (ET) is pivotal in calculating yield.

$$\frac{(Y_x - Y_a)}{Y_x} = K_y\left[\frac{(ET_x - ET_a)}{ET_x}\right] \quad (2)$$

where Yx and Ya are the maximum and actual yield, respectively; ETx and ETa are the maximum and actual evapotranspirations, respectively; and Ky is the proportionality factor between relative yield loss and relative reduction in evapotranspiration.

AquaCrop simulates crop yield in four steps: crop development, crop transpiration, biomass formation, and yield formation [40]. Four water stress response coefficients are considered in the model. These are related to canopy expansion, stomatal conductance, canopy senescence, and harvest index [67].

2.2.4. Soil Data and Calibration of the Crop Simulation Model

We retrieved the physical characteristics data of soils in Dapaong from Poss [68]. These measured soil physical characteristics were used as input into the Soil Water Hydraulic Properties Calculator (http://hydrolab.arsusda.gov/soilwater/Index.htm) to compute various soil hydraulic parameters required to run AquaCrop. We used this soil water hydraulic properties calculator because it has been employed in previous studies in the West African region (e.g., Akumaga et al. [69]). These include volumetric soil water content at field capacity, permanent wilting point, saturation, and saturated hydraulic conductivity (Table 2). Poss [68] classified the soil of Dapaong as sandy loam. According to the World Reference Base for Soil Resources, the soil in northern Togo is characterized by Dystric-Ferric Luvisols [70,71].

Table 2. The soil description and properties of Dapaong (See Poss [68]).

Soil Depth (cm)	Texture			OM (%)	dB (g/cm)	SAT (Vol.%)	FC (Vol.%)	PWP (Vol.%)	Ksat (mm/da)	Textural Class
	Sand (%)	Silt (%)	Clay (%)							
0–20	72.5	20.5	7.0	1.5	1.5	42.7	13.3	5.3	1252.6	Sandy Loam
20–50	72.0	19.0	9.0	0.9	1.6	40.8	13.5	5.9	503.0	Sandy Loam
50–110	66.5	18.0	15.5	0.7	1.6	39.9	18.3	10.0	239.5	Sandy Loam

FC, field capacity; PWP, permanent wilting point; SAT, saturation (SAT); Ksat, saturated hydraulic conductivity; dB, soil bulk density; OM, organic matter content in the soil.

Regarding the crop parameters, some of them were assumed to be conservative. The values of conservative parameters used in our study are the same as the values proposed by FAO [72] (not presented here). The others, non-conservative or crop-specific, were estimated using measured data retrieved from the ITRA [51], Didjeira et al. [52], and Worou and Saragoni [73] studies conducted in northern Togo (Table 4). These data were used to fine-tune the maize parameters to the local agronomic and management conditions of the study area before running the simulations in AquaCrop. These parameters include information about sowing, canopy cover, canopy senescence, flowering, rooting depth, harvest index, soil management, and the maize cultivar used. Regarding the calibration of the canopy cover, we used the options in AquaCrop to estimate the initial canopy cover (CCo) from sowing rate, seed weight, seed number and estimated germination rate. Subsequently, the canopy expansion rates were automatically estimated by AquaCrop after we entered the phenological dates such as dates of emergence, maximum canopy cover, senescence and maturity. The AquaCrop model simulations were run in growing degree day (GDD) calculated from temperature data used as climate input. Geerts et al. [74], Salemi et al. [75], and Silvestro et al. [76] reported on the most sensitive parameters in AquaCrop obtained through sensitivity analysis testing. The essential crop-specific parameters used to calibrate the AquaCrop model for simulating maize growth and productivity for the study area are presented in Table 3. It should be noted that the calibration of the AquaCrop model in this study is preliminary; thus the conclusions that emanated from the simulations are qualitative. The main idea was to compare the irrigation management strategies assessed in this study qualitatively.

Table 3. Non-conservative parameters adjusted and agronomic information for Dapaong, Togo.

Parameter Description	Value	Units or Meaning
Time from sowing to emergence	7 (135)	DAP(GDD)
Time to maximum canopy cover	60 (1109)	DAP(GDD)
Time from sowing to maximum rooting depth	67 (1257)	DAP(GDD)
Time from sowing to start of canopy senescence	76 (1408)	DAP(GDD)
Time from sowing to maturity	100 (1898)	DAP(GDD)
Time from sowing to flowering	54 (1018)	DAP(GDD)
Duration of flowering	10 (183)	DAP(GDD)
Length of building up HI	42 (778)	DAP(GDD)
Maximum effective rooting depth, Z	1	meter
Minimum effective rooting depth, Zn	0.3	meter
Reference harvest index, HI	50	%
Cultivar (TZEE-W)	–	TZEE-W
Planting method	–	Direct sowing
Planting density	62,500	Plants/ha
Soil fertility	65	Moderate (%)
Surface mulches	0	%
Curve number, CN	66	–
Readily Evaporable water, REW	2	mm

DAP, days after planting; GDD, growing degree days; HI, harvest index.

Table 4 summarizes the potential and selected sources of the input data used in this study and reasons for selecting these specific sources.

Table 4. Input data sources.

Type of Data	Possible Sources	Selected Sources for the Study	Reasons of Selecting Specific Sources for the Study
Temperature, rainfall, wind speed, and humidity	-Local meteorological station -Observed data online (NOAA, etc.) -Satellite data (NASA, etc.)	Local meteorological station	Observed data with no missing values
Solar radiation and sunshine hours	-Observed data online (NOAA, etc.) -Satellite data (NASA, etc.)	Satellite data (NASA-POWER project)	Publicly accessible, shows acceptable general agreement with ground data
Soil data	-Poss [68] -National soil survey -FAO Harmonized World Soil Database -ISRIC Soil Geographic Databases	Poss [68]	Publicly accessible and with good resolution (field)
Crop data: conservative parameters	AquaCrop manual	AquaCrop manual	In line with AquaCrop model
Crop data: non-conservative parameters	-AquaCrop manual -ITRA [51], Didjeira et al. [52], and Worou and Saragoni [73]	ITRA [51], Didjeira et al. [52], and Worou and Saragoni [73]	Specific to the maize variety used in the study

2.2.5. Optimal Irrigation Scheduling with Limited Water Supply

Matlab, AquaCrop interface, and Plugin-ACsaV40 (version 4; http://www.fao.org/aquacrop/en/) were used to simulate multiple projects for successive years. The soil and crop phenological data described in Tables 2 and 3, respectively, were used to calibrate AquaCrop. First, AquaCrop was run for a given amount of irrigation water for the maize crop under a specific climate scenario during the dry season of the Dapaong area. GET-OPTIS was employed as irrigation scheduling optimizer and crop yield maximizer. Then, we iterated over a range of given water volumes. As a result, a complete crop-water production function (CWPF) was derived. The 100-year maize crop simulations were run for the wet season as well as the dry season to assess the irrigation management strategies described above, in northern Togo.

3. Results and Discussion

3.1. Traits of the Climate in Dapaong

The temperature is high during the dry season reaching 37 °C and 26 °C maximum and minimum temperatures, respectively, while, in the wet season, the maximum temperature is 30 °C and the minimum temperature is close to 26 °C (Figure 4a). Due to these high temperatures, especially in the dry season, it is likely that the evapotranspiration is relatively high in the area. This argument is corroborated by Djaman and Ganyo [77] who found that the potential annual reference evapotranspiration—computed using the FAO-56 Penman–Monteith method—in northern Togo is higher than 1800 mm on average.

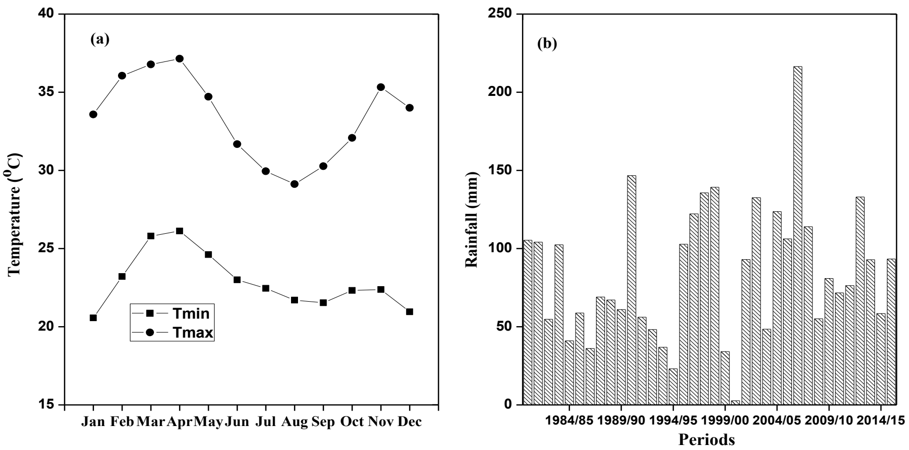

Figure 4. (**a**) Monthly mean temperature; and (**b**) mean total rainfall from November to April in Dapaong, Togo (1980–2016).

Figure 4b depicts the mean total rainfall during the dry season (November–April) in Dapaong district. The rainfall recorded during the dry season varies significantly from year to year. On average, the total rain that falls within this period is lower than 85 mm. In some years, the volume of rain which falls in the same period is up to 100 mm. The highest amount was reached in 2006/2007 (216 mm). Globally, this rainfall occurs on an average of five days only. Thus, none of the main cereals grown in the area such as maize, millet, and sorghum can survive under the dry season climatic conditions without an additional water supply. These findings prove again the fact that farmers only grow crops during the wet season. Overall, the climate of Dapaong in northern Togo is unfavorable to agricultural activities throughout the year because of its vagaries and uncertainties compromising crop yield. These results are in agreement with studies by Ogounde and Abotchi [16].

3.2. Validation and Application of the LARS Weather Generator

The LARS-WG model showed robust compliance between observed and simulated data for the maximum as well as minimum temperatures (Table 5). These findings showed no significant differences between the observed and simulated temperatures for all months. All p-values were close to one. It means that the observed and simulated data were from the same distribution. Therefore, based on these results, we conclude that the performance of the LARS-WG model in simulating the climatic variables such as minimum and maximum temperatures of Dapaong district is satisfactory. Similar results were obtained by Semenov et al. [60] at 18 sites in the USA and Europe. However, the standard deviations of the monthly mean simulated values are less than half of the standard deviations of observed values for all months. This means that the extreme temperature values in the minimum and maximum temperatures simulated are smaller than in the observed data.

The observed and simulated rainfall values for most of the months do not correlate significantly (Table 5). This result agrees with studies by Osman et al. [78] in Iraq. However, there are significant differences between December and January, when LARS-WG was incapable of reproducing the observed rainfall, partly because these periods are the driest during the dry season. The standard deviations of the monthly mean rainfall of observed and predicted values are similar for January, February, and April (Table 5). These results imply that there are fewer extreme rainfall values in the dry months, which are of our interest in this study. Overall, the performance of LARS-WG in predicting the rainfall of the Dapaong area is at an acceptable level. It means that the quality of the long-term data that were generated based on these calibration results is not affected.

3.3. Evaluation of Irrigation Management Strategies

3.3.1. Wet Season—Rainfed and Supplemental Irrigation Systems

- *Maize Crop under Rainfed Conditions (WS-NI)*

While Figure 5a shows the results of the expected maize crop yields that can be achieved during the rainfed cropping system, Figure 5b portrays the rainfall statistics within the same period. The volume of rainwater that falls within the cropping period of the wet season in Dapaong ranges from 450 mm to 1100 mm approximately. The frequency of the rainfall is high, between 600 mm and 900 mm (Figure 5b). The distribution of the expected rainfed yields is moderately skewed left with a higher coefficient in absolute values (1.91) (Figure 5a). The standard deviation of the expected yields obtained under rainfed conditions is higher than in the case of irrigated maize, regardless of the volume of water used, in northern Togo (See section 3.3.2). These results show that the variability, as well as the uncertainty, in the yields, are higher under the rainfed conditions (WS-NI) than under the dry season CDI and FI. The high variability under rainfed conditions is likely due to inadequate rainfall distribution and dry spells in the wet season [79]. On average, the expected maize crop yield achieved in the wet season is 3.5 Mg/ha (Figure 5a). These results agree with the findings by Didjeira et al. [52] who indicated the range of 3.5–5 Mg/ha as the expected yield for the maize variety used in this study. Similarly, these results are in line with that of Fosu-Mensah [80] who reported that in sub-humid Ghana under projected climate change (2030–2050) for scenario A1B of IPCC, the rainfed maize grain yield varies from 3.16 Mg/ha to 4.09 Mg/ha. Therefore, the calibrated AquaCrop model in this study performs well. These results can be improved if data on more site-specific parameters are made available. Akumaga et al. [69] suggested that the AquaCrop model can be utilized as a tool in the study and modeling of maize productivity in the West African region.

Table 5. Kolmogorov–Smirnov test statistics for rainfall, maximum and minimum temperatures in Dapaong.

Month	RAINFALL				MAXIMUM TEMPERATURE				MINIMUM TEMPERATURE			
	SD of Observed Data	SD of Simulated Data	K-S	*p*-Value	SD of Observed Data	SD of Simulated Data	K-S	*p*-Value	SD of Observed Data	SD of Simulated Data	K-S	*p*-Value
January	0.11	0.17	0.57	0.00	1.34	0.46	0.11	1.00	1.60	0.52	0.05	1.00
February	14.89	13.89	0.17	0.84	1.24	0.41	0.16	0.91	1.66	0.48	0.11	1.00
March	19.53	31.90	0.15	0.94	0.73	0.28	0.11	1.00	1.04	0.36	0.16	0.91
April	44.99	43.27	0.11	1.00	0.95	0.43	0.11	1.00	0.84	0.43	0.11	1.00
May	38.39	44.09	0.05	1.00	1.25	0.40	0.11	1.00	0.83	0.38	0.11	1.00
June	54.58	53.28	0.03	1.00	0.89	0.32	0.05	1.00	0.72	0.30	0.05	1.00
July	69.68	85.13	0.05	1.00	0.72	0.37	0.05	1.00	0.57	0.26	0.05	1.00
August	85.44	99.96	0.06	1.00	0.60	0.30	0.05	1.00	0.57	0.26	0.11	1.00
September	61.77	68.39	0.08	1.00	0.58	0.37	0.05	1.00	0.58	0.25	0.05	1.00
October	43.20	57.00	0.01	1.00	1.04	0.40	0.11	1.00	0.83	0.27	0.05	1.00
November	12.00	15.73	0.13	0.98	0.83	0.26	0.11	1.00	1.34	0.34	0.11	1.00
December	5.66	10.98	0.26	0.36	1.04	0.43	0.05	1.00	1.38	0.44	0.05	1.00

SD, standard deviation; K-S, Kolmogorov-Smirnov test coefficient.

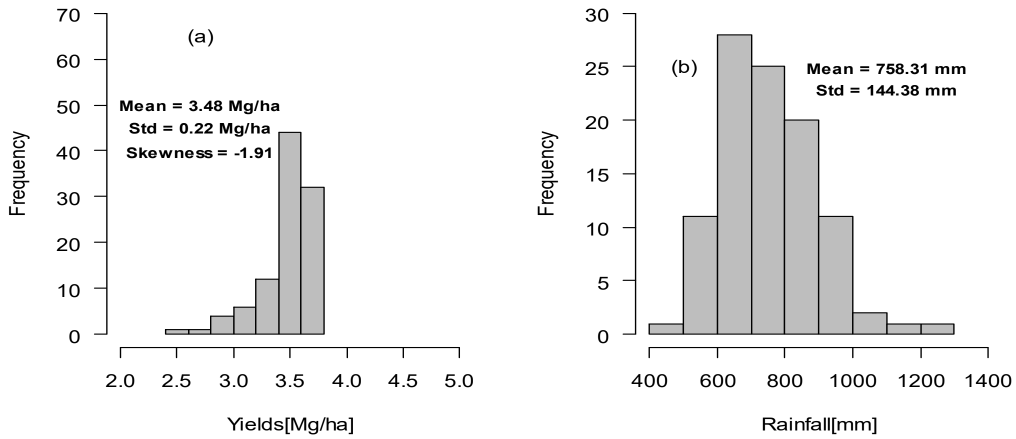

Figure 5. Histogram of distributions of: (**a**) expected yield of maize grown in a rainfed system (WS-NI); and (**b**) the rainfall during the wet season in Dapaong.

➢ *Maize under Supplemental Irrigation (WS-CDI and WS-FI)*

To improve yield while reducing its variability at the same time, one may apply supplemental irrigation during the rainfed cropping system whenever the crops are experiencing severe water stress, and rainfall is not occurring. The stochastic crop-water production functions for supplemental irrigation conditions are shown in Figure 6a. It can be hypothesized that, when more than 150 mm supplemental irrigation water is applied, the variation in the resulting expected crop yield is likely due to the variation of temperature and radiation in the area. These assumptions are supported by the nearly symmetric distributions of the corresponding expected crop yields (Figure 6a). Besides, at volumes of supplemental water lower than 150 mm, the variation in the expected crop yield can result from the combined effects of the uneven distribution of rainfall and the climate parameters mentioned above. The 90% of SCWPF exceedance probability of yield achievement seems to be the best option for enhancing food security in northern Togo. This might be because it is the only option which helps to achieve the highest level of crop yield improvement (15% or more) (Figure 6a). Applying supplemental irrigation in northern Togo for maize crop cultivation will not only contribute to improving crop grain yield and enhancing food security [81–83] but also help to improve farmers' livelihood. Nevertheless, supplemental irrigation alone cannot improve the rainfed yields significantly; it needs to be combined with other field management aspects such as soil preparation and fertility, pests and diseases management, and the choice of suitable crop varieties. It can be concluded that CWPF is a useful planning tool to assess water requirement for crops, especially in water-scarce regions. Heng et al. [84] and Stricevic et al. [85] reported that, due to its sufficient degree of simulation accuracy, the AquaCrop model is a valuable tool for estimating crop productivity under rainfed conditions, deficit and supplemental irrigation, and on-farm water management strategies for improving the efficiency of water use in agriculture.

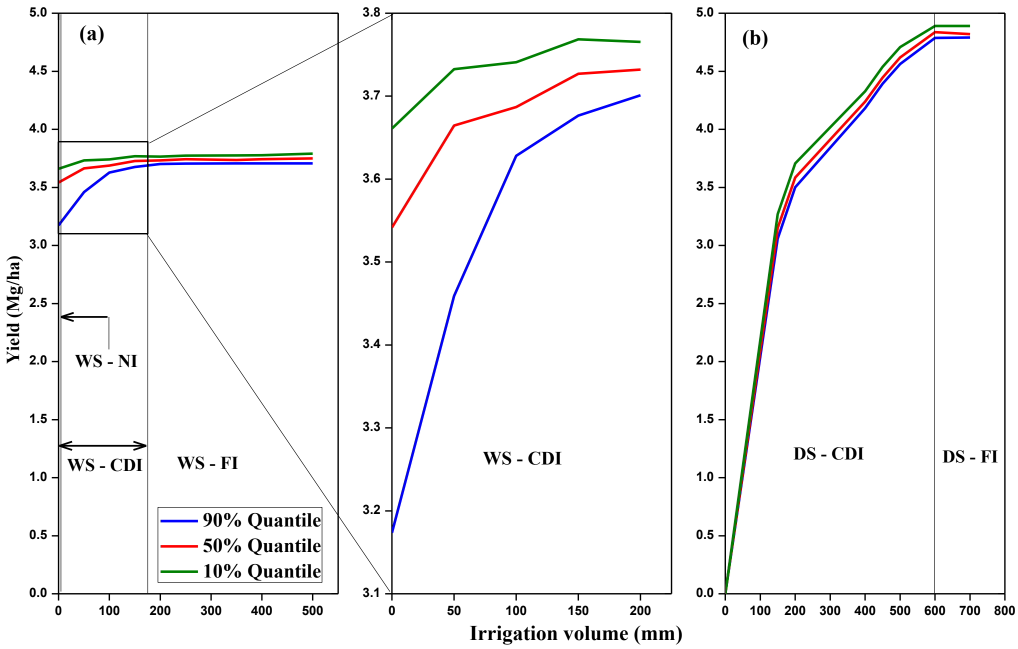

Figure 6. Stochastic crop-water production function for: (**a**) rainfed and supplemental irrigated systems in the wet season; and (**b**) optimized conventional irrigation system in the dry season for maize in Dapaong.

Figure 7 shows the detailed results of the expected yields at various amounts of supplemental irrigation water. With supplemental irrigation (WS-CDI), the rainfed yield increased from 3.48 Mg/ha to 3.74 Mg/ha. The yield becomes constant when the volume of water applied is equal to or greater than 150 mm. Then, the variability in the yields as well as the skewness decreases in absolute value. These results imply that supplemental irrigation is beneficial up to 150 mm. Above this value, the advantages of supplemental irrigation (WS-FI) become insignificant. Therefore, rainfed maize crop yields may be improved in northern Togo by applying supplemental irrigation, assuming that water is available.

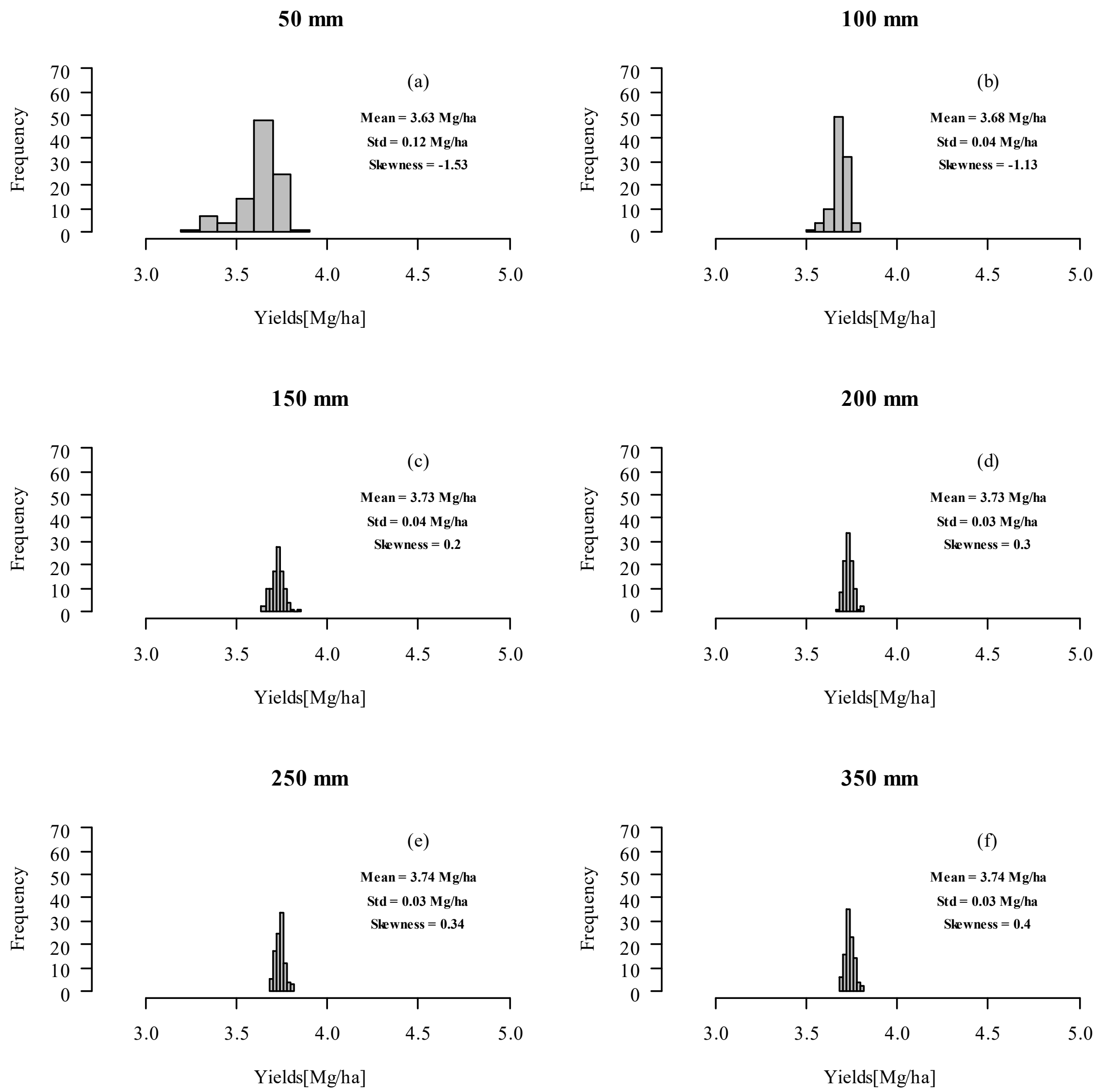

Figure 7. Histogram of distributions of expected yield using water for supplemental irrigation of maize in the wet season in Dapaong: (**a**) 50 mm; (**b**) 100 mm; and (**c**) 150 mm (WS-CDI); and (**d**) 200 mm; (**e**) 250 mm; and (**f**) 350 mm (WS-FI).

3.3.2. Dry Season—Conventional Irrigation System (DS-CDI and DS-FI)

Figure 6b shows the stochastic crop-water production functions (SCWPF) for optimized irrigated maize crop in the dry season in northern Togo. The quantile percentage represents the probability of exceedance. Since rainfall can be ruled out, it is believed that, when the optimal full irrigation conditions are met, the variation of temperature and radiation can explain the variability in the expected crop yield. These assumptions are corroborated by the nearly symmetric distributions of the expected crop yields at full irrigation (Figure 8). These findings are supported by the results presented by Schütze and Schmitz [36]. These two parameters are part of the yield defining factors, as highlighted in the papers explaining the principles of ecology production [86]. In addition, for volumes of water lower than full irrigation, the variation in the expected crop yield can result from the combined effects of drought stress on crops and the climate parameters mentioned above. The maximum expected yields were 4.79 Mg/ha (90% quantile) and 4.89 Mg/ha (10% quantile) at near full irrigation (600 mm) (Figure 6b). The controlled deficit irrigation ranges from 0 to 600 mm for maize in northern Togo. The DS-CDI strategy seems to save water with an insignificant reduction in the grain yield relative to full irrigation [87–92]. Overall, growing maize crop in the dry season in northern Togo may be feasible under CDI if water is available. Irrigation is vital for improving crop yield and stabilizing crop production [93] amidst the threats of climate change [94].

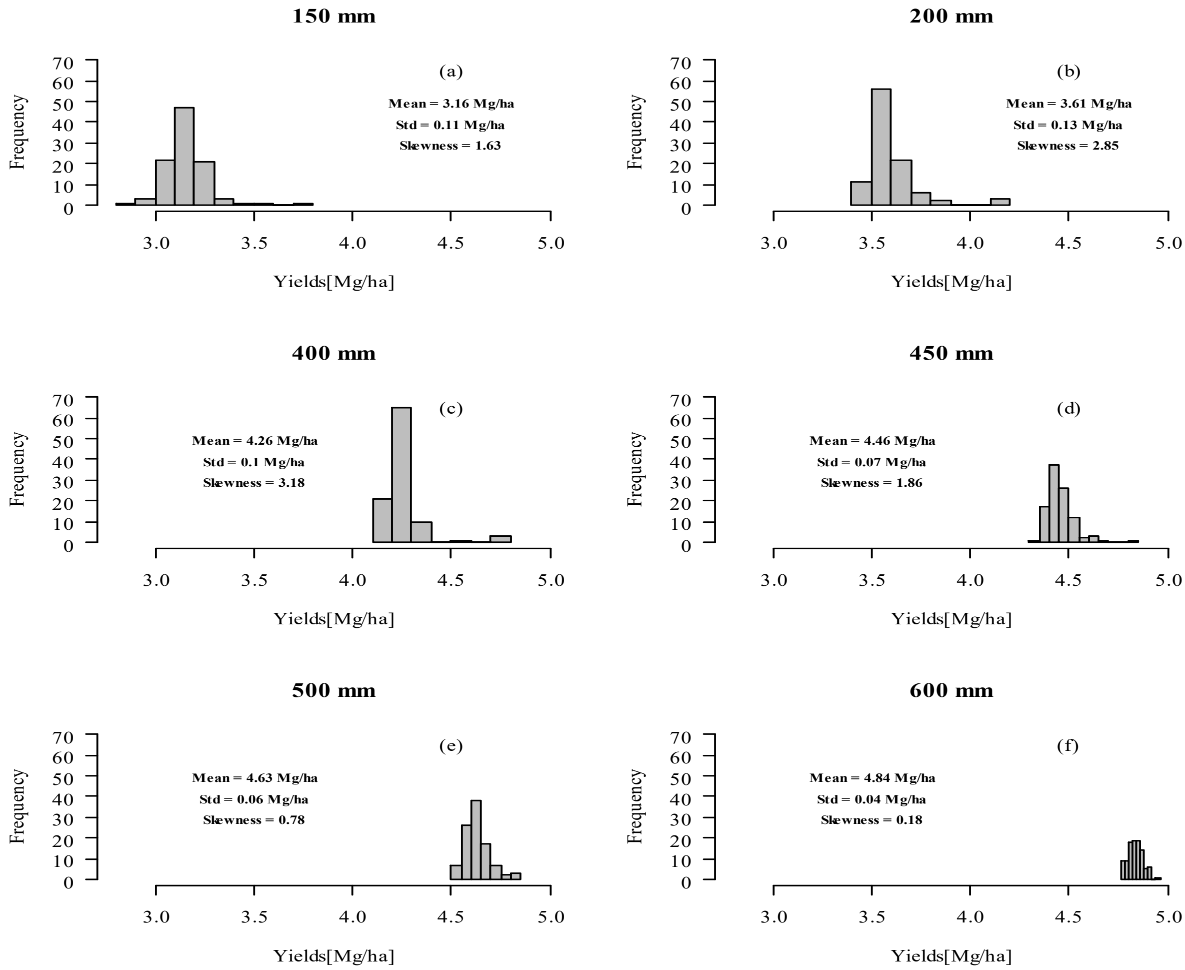

Figure 8. Histogram of distributions of expected yield using water for irrigation of maize in the dry season in Dapaong: (**a**) 150 mm; (**b**) 200 mm; (**c**) 400 mm; (**d**) 450 mm; and (**e**) 500 mm (DS-CDI); and (**f**) 600 mm (DS-FI).

In Figure 8, detailed results of the expected yields at various amounts of irrigation water are given. There is a change in the histogram distribution among the various volumes of irrigation water. The average expected yields concerning the amount of irrigation water used range from 3.16 Mg/ha to 4.84 Mg/ha at 150 mm and 600 mm, respectively. With the increasing application of irrigation water (DS-CDI), the yield increases to a level at which additional water supply fails to raise the crop yield any further (around 600 mm). Thus, the latter volume of water is assumed to be near full irrigation. The frequency distribution shows a positive sign for all the histograms. The coefficients of skewness of the expected yields for 150 mm, 200 mm, and 400 mm water volumes are 1.63, 2.85, and 3.18, respectively. On the contrary, at 600 mm volume of water (DS-FI), the distributions of the expected yields are symmetrical. In addition, the standard deviation is relatively low for the yields at these volumes of water.

Abedinpour et al. [95] reported that the AquaCrop model could predict maize yield with acceptable accuracy under variable irrigation in a semi-arid environment.

3.4. Summary of the Discussion

The variability in rainfall during the wet season (WS-NI) was high, inducing a considerable variability in the expected yield for rainfed conditions. The variability in the expected yield would decrease significantly if supplemental irrigation (WS-CDI or WS-FI) were applied. At the same time, supplemental irrigation would improve the expected yields and contribute to avoiding crop failure. The dry season irrigation management strategies (DS-CDI and DS-FI) would increase yield potential and decrease the variability of expected yield at the same time. Thus, the application of supplemental or dry season irrigation management strategies investigated in this study would help to enhance food availability in the West African region.

There are a few caveats that readers should keep in mind when interpreting the results of this study: The AquaCrop model in this study was calibrated with crop and soil data retrieved from previous studies conducted in the area. Thus, the conclusions derived from the outputs of the model simulation are qualitative—ranking of the irrigation management strategies assessed in the study. There are several uncertainties in the general circulation model outputs as well as crop model simulations. The uncertainties related to crop yield exist because AquaCrop assumes a disease- and pest-free environment and considers no effect of weed or extreme climate events such as flooding. Another point worth considering is that, by concluding that there is potential for the deficit and supplemental irrigation for maize crop in northern Togo, we assumed that a proper soil fertility management is guaranteed, and water is available for irrigation management. Finally, it is important to note that substantial investments in irrigation infrastructure, as well as extension services to farmers, would be necessary to enhance food security in northern Togo. The calibrated crop model needs to be validated with experimental data to improve the accuracy of the resulting simulations.

4. Conclusions

The AquaCrop model was used to assess the potential of deficit and supplemental irrigation in the dry savannah area of northern Togo under climate variability. For this, the climate of the study area was characterized. The performance of the weather generator used to produce the long-term time series climate data for the crop simulation was also evaluated. In summary, the climate of northern Togo is unimodal with the dry season ranging from November to April. According to Köppen–Geiger's classification, the climate is hot semi-arid in northern Togo. During the dry season, the mean maximum and minimum temperatures are 35 °C and 25 °C, respectively, and the mean total rainfall is 85 mm. In short, the performance of the LARS Weather Generator in predicting the climate of northern Togo was found satisfactory. Overall, we found that the deficit irrigation water requirement ranges from 0 to 600 mm. The maximum expected maize grain yield that can be reached under irrigated conditions is 4.84 Mg/ha with TZEE-W local variety. The rainfed yield can be improved from 3.48 to 3.74 Mg/ha with 150 mm of supplemental irrigation water. At the same time, the variability in the yield was significantly reduced. Irrigation practice in agriculture helps to lower crop yield variability as well as crop failure.

Thus, growing maize crop in the dry season in northern Togo may be feasible. In general, irrigation can help to alleviate food insecurity, while supplemental irrigation is a climate-related management practice for crop yield improvement. The latter also contributes to improving farmers' livelihood. Further maize crop genetic improvements would be needed to fine-tune the seeds to the dry season climate. Irrigation infrastructures would be needed to implement in northern Togo the irrigation management strategies investigated in this study. In addition, realistic irrigation water pricing and cost recovery policies should be enforced and followed by all stakeholders to maintain the irrigation infrastructures and ensure the viability of the system. Institutional reforms relevant to the development and management of irrigation systems should be made. The complicated land tenure issue in northern Togo needs to be addressed to incentivize investment in, and management of, irrigation systems.

Moreover, the institutional arrangement—market and connectivity among farmers and other agents—should be improved.

To develop regional water management strategies, the adapted framework used in this study may be applied to other sites in the West African region. Field experiments are needed to validate the results of this study before the implementation of its recommendations. In addition, the framework can be extended by adding a soil variability dimension to it. The analysis can be made more comprehensive by considering farmers' socioeconomic characteristics.

Author Contributions: A.G.-T. and N.S. developed the concept and design of the numerical experiment. A.G.-T. carried out the simulations, analyzed the data, and wrote the manuscript; T.A. and N.S. critically reviewed the manuscript. All authors revised and approved the final manuscript.

Funding: This research was supported by a grant to A.G.-T. PhD scholarship under the Merit Scholarship Programme (MSP) 2015/2016 of the Islamic Development Bank (IsDB).

Acknowledgments: This research received logistical assistance from the United Nations University Institute for Integrated Management of Material Fluxes and Resources (UNU-FLORES) and Technische Universität Dresden (TU Dresden), Germany. We extend our thanks to the administration of the national meteorological service of Togo for providing us with the climate data. Our gratitude goes to the editor and anonymous reviewers whose comments and suggestions expressively contributed to the improvement of this paper. Our thanks also go to Atiqah Fairuz Salleh for her editorial input to the manuscript.

Conflicts of Interest: The authors have no competing interests to declare.

Appendix A

List of Abbreviations

APSIM	Agricultural Production Systems Simulator
CDI	Controlled Deficit Irrigation
CWPF	Crop-Water Production Functions
DAISY	Danish simulation model for transformation and transport of energy and matter in the soil plant atmosphere system
DAP	Days After Planting
DI	Deficit Irrigation
DS	Dry Season
DSSAT	Decision Support System for Agrotechnology Transfer
FI	Full Irrigation
GET-OPTIS	Global Evolutionary Technique for OPTimal Irrigation Scheduling
GDD	Growing Degree Days
HI	Harvest index
ICID	International Commission on Irrigation and Drainage
IPCC	Intergovernmental Panel on Climate Change
ISRIC	International Soil Reference and Information Centre
ITRA	Togolese Institute of Agricultural Research
LARS-WG	Long Ashton Research Station Weather Generator
MERF	Togolese Ministry of the Environment and Forestry
NI	No Irrigation
OCCASION	Optimal Climate Change Adaption Strategies in Irrigation
PILOTE	An operative crop model for soil water balance and yield estimations under conventional tillage
REW	Readily Evaporable Water
SCWPF	Stochastic Crop-Water Production Functions
SI	Supplemental Irrigation
SSA	Sub-Saharan Africa
WGEN	Weather Generator
WS	Wet Season

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A.2 Impact of Irrigation Strategies on Maize (*Zea mays L.*) Production in the Savannah Region of Northern Togo (West Africa)

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ABSTRACT

In northern Togo where rainfed maize is one of the major crops grown, agriculture is subject to frequent yield losses due to erratic rainfall. To ensure food availability and improve the agricultural productivity, it is necessary to produce maize during the dry season under irrigation. A sound application of full and deficit irrigation requires a thorough understanding of the crop parameters and yield response to water. Thus, this study investigated the effect of full and deficit irrigation on maize plant above-ground biomass, leaf area index, canopy cover, plant height, and grain yield. A field experiment was carried out from December 2017 to April 2018 in northern Togo at the agronomic research institute. Full irrigation (FI), 80% FI, and 60% FI treatments were applied. The results showed that in the late-season stage, the differences in the biomass between the FI and 60% FI were significant ($p < 0.05$). On average, the FI had the greatest grain yield (2,200.4 kg/ha), while the lowest grain yield was recorded under the 60% FI (1,068.3 kg/ha). The grain yield differences between FI and 60% FI were significant. Nevertheless, the grain yield differences between FI and 80% FI were not significant ($p > 0.05$). The 80% FI had Water Use Efficiency (WUE) (0.22 kg/m^3) similar to that of FI (0.21 kg/m^3) on average. The results of this study illustrate that deficit irrigation must be carefully managed since slight differences in the application volumes affect the biomass and yield of maize significantly. Under a moderate level of deficit irrigation (vegetative and reproductive growth stages) the biomass and the grain yield of maize are reduced. However, a moderate level of deficit irrigation during the vegetative growth stage could result in similar values of WUE to that of FI.

Keywords: evapotranspiration; deficit irrigation; water use efficiency; crop yield; maize

INTRODUCTION

The world population is growing persistently, and people's desire for higher living standards is also increasing (UN DESA, 2015). As a result, there is a change in diet towards more meat and dairy products consumption in the developing world (Kearney, 2010). This situation is putting more stress on water resources all over the world, especially in arid areas (Rosegrant, 2016). In West Africa, the population will increase by more than two-fold by 2050 (UN DESA, 2017). At the same time, the demand for cereals will almost triple, while the present levels of cereal consumption already rely on considerable imports (van Ittersum et al., 2016). Liniger et al. (2011) reported that, in the region, to meet the necessary caloric requirements, food production should increase by 70% by 2050. However, the agricultural sector has been subject to numerous obstacles, including water-related challenges.

Owing to the growing population, the pressure on water bodies has increased. Thus, the quality and quantity of water that can be used in agriculture for irrigation has decreased in the West African region (Kotir, 2011). Additionally, this region has been described as one of the most sensitive regions to the impacts of climate variability and change because of its dependence on rainfed agriculture (Kotir, 2011). There is a change in the seasonal distribution and intensity of rainfall as well

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as an increase in the temperature in the region (Lobell and Gourdji, 2012). Thus, to be able to feed the increasing population, we need to produce higher crop yields with a limited amount of water. Within this context, deficit irrigation might be a strategy for addressing the issue in West Africa. Deficit irrigation practices could contribute to enhancing crop productivity in the area (Djaman et al., 2013).

Djaman et al. (2013) pointed out that limited irrigation can lead to considerably different productivity in various climate conditions. For instance, Howell et al. (1995) reported that limited irrigation of maize decreased yields by affecting the kernel weight and the number of kernels per ear in the semi-arid region of Bushland, Texas. Similar findings were obtained by Pandey et al. (2000a) in the Sahelian environment of Niger. Deficit irrigation and water stress affected maize grain yield significantly under semi-arid climate condition in the south-west of Iran (Khaksar et al., 2013). Farré and Faci (2006) indicated that maize phenology, crop water uptake, total above-ground biomass, and yield were significantly affected by the irrigation treatments in the semi-arid conditions of Northeast Spain. The AquaCrop model has shown good performance in evaluating the effects of deficit irrigation on maize production under diverse environmental conditions including a semi-arid climate (Ahmadi et al., 2015).

Didjeira et al. (2007) identified maize as the staple food in Togo, as it represents 60% of the cereals consumed by the population in Togo. In northern Togo, where there is only one rainy season annually, to provide maize throughout the year, some farmers are cultivating it under limited irrigation in the dry season. These farmers receive little help from the scientific research community. The correct application of limited irrigation requires a thorough understanding of the crop parameters and yield responses to water. The knowledge of a locally developed crop parameters response to different irrigation water levels is essential for effective on-farm limited irrigation management practices (Djaman et al., 2013). However, few studies have been conducted to assess crop yield response to water in Togo, especially for the northern part.

This study assesses the maize crop response to several variables under full and limited irrigation conditions. Specifically, the study aimed to (i) quantify the effect of limited irrigation management practices on maize plant height, above-ground biomass, leaf area index (LAI), green canopy cover (CC), and yield; and (ii) evaluate the deficit irrigation stress index of these maize crop parameters concerning the growth stages.

DATA and METHODS

Site description

The study was conducted in Northern Togo, at ITRA (Institut Togolais de Recherche Agronomique) research station (10°52′49.13″ N, 0°11′31.90″ E, 295 m above sea level) (Figure 1). The climate is hot semi-arid (BSh) according to Köppen-Geiger's climatic classification (Kottek et al., 2006). The cropping season in the area lasts from May to October. The dry season ranges from November to April. Climate data (1983–2011) used were collected from the Dapaong climate station located 5 km away from the experimental site, which is the closest station.

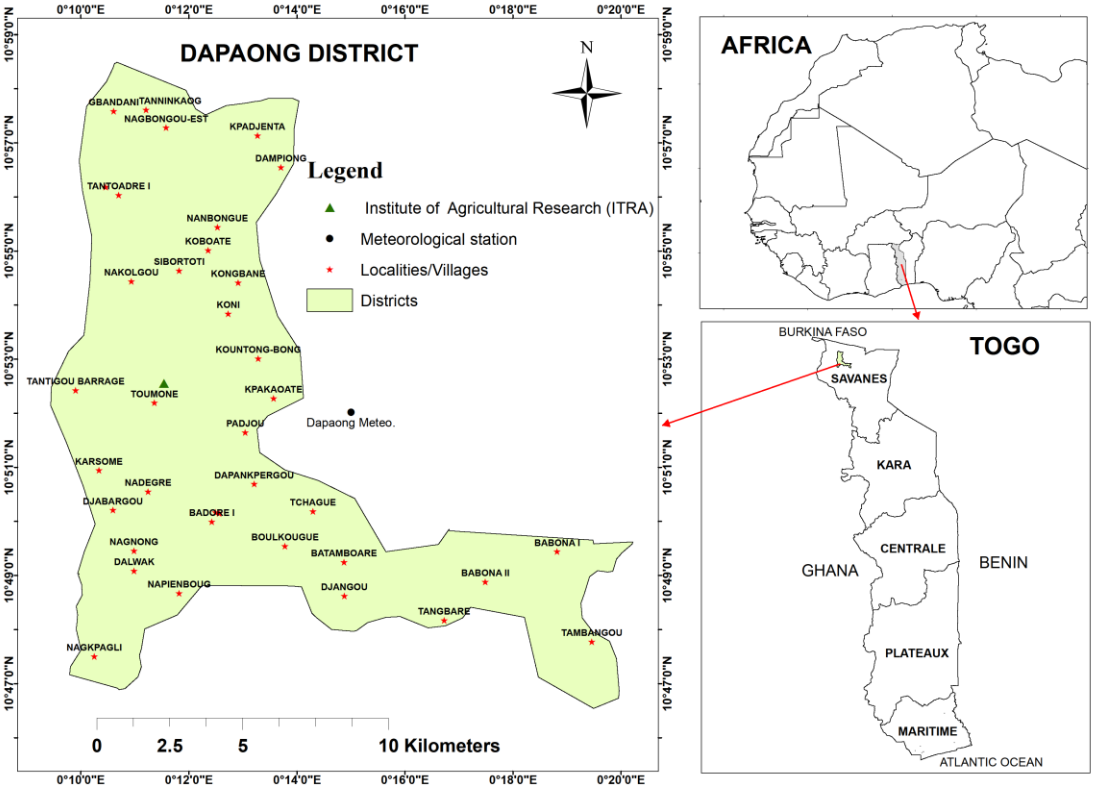

Figure 1
Map of northern Togo indicating the study area (Dapaong district)
(Source: Authors of the study)

Experimental design

The experiment was carried out during the dry season from November 2017 to April 2018. The local maize crop short cycle variety (TZEE-W) was used for the experiment. TZEE-W has a growth cycle of 90-95 days and an average dry grain yield of 2,000 kg/ha (Didjeira et al., 2007). The experiment consisted of three irrigation treatments, replicated three times, arranged in a randomised complete block design (RCBD). There was a total of 9 plots of 20 m^2 each, manually ploughed. Two meters width were shaped around the perimeter of each parcel as a buffer to avoid border and interaction effects.

Irrigation treatments

The treatment designs are of a single factor, where the treatment variation was based only on the volume of irrigation water applied and the irrigation scheduling. The water was applied using a micro-sprinkler system. The three irrigation levels included a full irrigation (FI) treatment and two deficit treatments as follows:

- The FI treatment

$$V_{FI} = \sum q_i \qquad (1)$$

where V represents the total volume of water utilised; q is the amount of water applied for an event i.

- The first deficit treatment is Optimized Controlled Deficit Irrigation (OCDI). It consisted of 80% of the total volume of FI.

$$V_{OCDI} = 80\% V_{FI} \qquad (2)$$

- The second deficit treatment is Controlled Deficit Irrigation (CDI). It consisted of modifying the schedule of the FI by applying 60% of the volume water of each irrigation event.

$$V_{CDI} = \sum 60\%\, q_i \qquad (3)$$

Figure 2 shows the framework used to generate the OCDI schedule for our experiment. This framework consists of: (i) a weather generator, the Long Ashton Research Station Weather Generator (LARS-WG) (Semenov et al., 1998) for simulating long climate time series; (ii) the AquaCrop model (Hsiao et al., 2009) which was used to simulate the irrigation system during the cropping season (Figure 2, loop 1); and (iii) a problem-specific programme for optimal irrigation scheduling under limited water supply (Figure 2, loop 2). The latter is named Global Evolutionary Technique for OPTimal Irrigation Scheduling (GET-OPTIS) (For more details, see Schütze et al., 2012). A maximum volume of water is given to GET-OPTIS, which produces an optimised irrigation schedule based on the climate, soil, and crop information provided. Then, this schedule is used by AquaCrop version 5.0 for the yield prediction. A 100-year simulation was run using the same climate data and calibrated maize crop information from Gadédjisso-Tossou et al. (2018). The details of the observed meteorological data from the nearest station used in this study and the calibration details are reported in Gadédjisso-Tossou et al. (2018). The input data of crop parameters used in the AquaCrop model are presented in Table 1.

TABLE 1
Input data of crop parameters used in the AquaCrop model

Parameter Description	Value	Units or Meaning
Base temperature	10	°C
Cut-off temperature	30	°C
Canopy cover per seedling at 90% emergence (CC_0)	6.5	cm^2
Time from sowing to emergence	7 (135)	DAP(GDD)
Time to maximum canopy cover	60 (1109)	DAP(GDD)
Time from sowing to maximum rooting depth	67 (1257)	DAP(GDD)
Time from sowing to start of canopy senescence	76 (1408)	DAP(GDD)
Time from sowing to maturity	100 (1898)	DAP(GDD)
Time from sowing to flowering	54 (1018)	DAP(GDD)
Duration of flowering	10 (183)	DAP(GDD)
Length of building up HI	42 (778)	DAP(GDD)
Maximum effective rooting depth, Z	1	m
Minimum effective rooting depth, Zn	0.3	m
Reference harvest index, HI	50	%
Cultivar (TZEE-W)	–	TZEE-W
Planting method	–	Direct sowing
Planting density	62,500	Plants/ha
Soil fertility	65	Moderate (%)
Surface mulches	0	%
Curve number, CN	66	–
Readily Evaporable water, REW	2	mm

DAP = Days After Planting; GDD = Growing Degree Days; HI = Harvest Index.

Since the simulations were done stochastically, an exceedance probability of 0.9 was used to reach a given maximum level of yield. Based on these simulations, the best optimised general irrigation schedule was obtained and implemented during our field experiment as OCDI. The schedule of FI treatment was also obtained from the crop simulation but without applying GET-OPTIS.

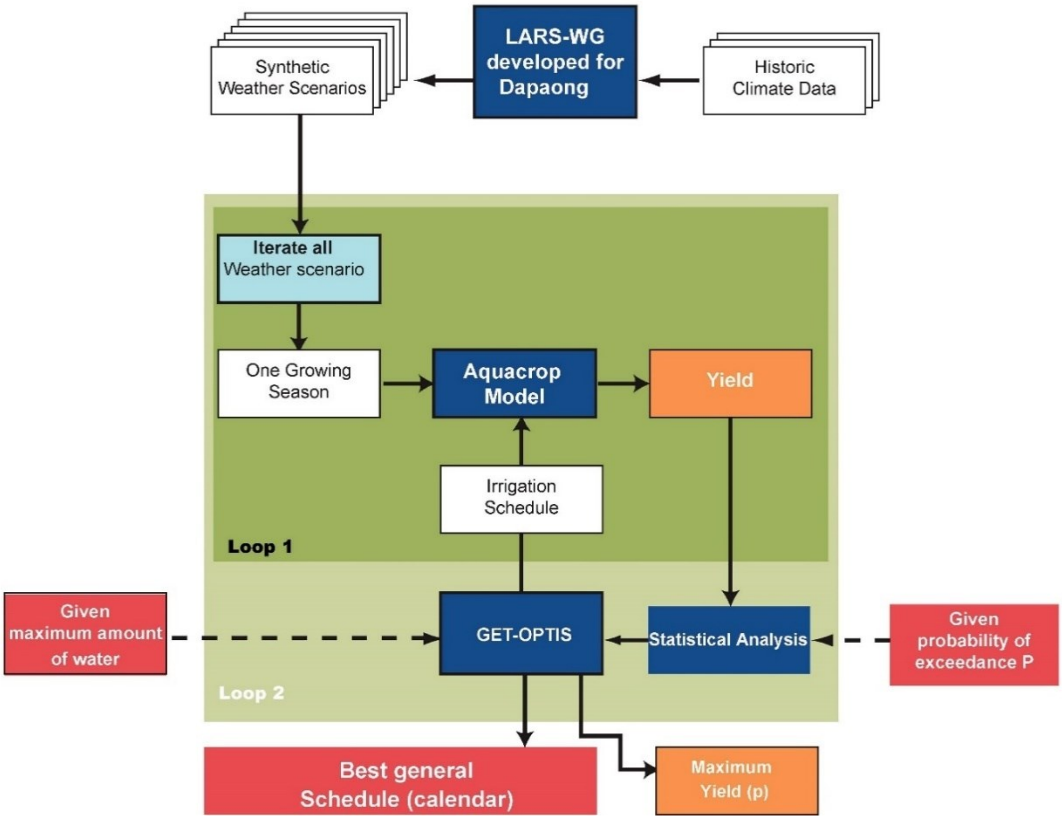

Figure 2
General framework for generating the Optimized Controlled Deficit Irrigation schedule (adapted from Schütze and Schmitz (2010) and. Gadédjisso-Tossou et al. (2018))

The FAO Penman-Monteith method was employed to calculate the reference evapotranspiration (ET_0) [mm/day] throughout the growing season. The crop coefficient of maize (K_c) for specific growth stages was retrieved from FAO-56 standard values (Allen et al., 1998). These values were adjusted to the climate of the experimental site (semi-arid) and are similar to the values reported by Abdulmumin and Misari (1990) for maize in semi-arid tropics of Nigeria, West Africa.

- Initial stage (25 days): K_c ini = 0.5;
- Crop development stage (30 days): K_c dev = 0.85;
- Mid-season stage (40 days): K_c mid = 1.2;
- Late season stage (15 days): K_c end = 0.9.

Then, the K_c was used to compute the crop evapotranspiration (ET_c) [mm/day] throughout the cropping period of the experiment. The ET_c was calculated as follows (Allen et al., 1998):

$$ET_c = K_c \times ET_0 \quad (4)$$

The FI, 80% FI, and 60% FI treatments represent 1.4 ET_c, 1.1 ET_c, and 0.8 ET_c, respectively.

Crop management practices

During the experiment, crops were exposed to the same field management practices, which follow the recommendation of ITRA. The maize seeds were sown with an inter-row distance of 0.8 m. The spacing within the rows was 0.35 m. Three seeds were put in each hole, then separated and adjusted to 2 plants per hole after emergence. This resulted in a plant density of 70,000 plants per hectare. All plots were fertilised equally. A composite fertiliser N15P15K15 was applied at the rate of 200 kg/ha on the 15th day after sowing. Moreover, the urea (46% N) was utilised at the rate of 100 kg/ha on the 35th day after sowing (Mathe et al., 2008). The fertilisers were manually point-placed at approximately 0.05 m depth and 0.07–0.1 m distance from the plants. The plots were weeded at the time of fertiliser application to avoid the competition between the maize plants and weeds for light, nutrients, or water. Insects and diseases were rigorously controlled for the experiment to avoid crop failure and reduction in yield. Therefore, insecticide (EMACOT 050 WG: emamectin benzoate 50 g/kg) and fungicide (Calthio C 50 WS: thiram 25%, chlorpyrifos-ethyl 25%) were applied uniformly to all plots when needed.

Soil characteristics and infiltration measurements

Table 2 shows the essential soil physical characteristics of the experimental site, the initial soil water content and the hydraulic properties for the experiment. The soil samples were taken at two points horizontally on a diagonal of the plots. Four soil depths were considered. Thus, eight soils samples were taken from each plot. The soil organic matter was measured in the laboratory using the modified Walkley-Black method (Walkley and Black, 1934). The soil texture was determined by mechanical analysis using the pipette method (DIN ISO 11277) (International Organization for Standard, 2009). We followed the United States Department of Agriculture soil textural classification system (USDA, 1987). The soil moisture was determined on all plots at the beginning and the end of the experiment using the gravimetric method. The soil at the experimental field is classified as sandy loam, according to the World Reference Base for Soil Resources, dystric-ferric luvisols (IUSS Working Group WRB, 2015) (Table 2). The soil is relatively poor in organic matter at the top 0.1 m.

TABLE 2
Soil physical properties of the experimental site and initial soil water content at different soil depths

Soil Depth (m)	Bulk density (kg/m³)	Organic matter (%)	Sand (%)	Silt (%)	Clay (%)	Initial Soil water content (% Volume)	Field capacity (% Volume)	Permanent wilting point (% Volume)	Saturated hydraulic conductivity (mm/day)	Textural Class
0-0.1	1,580 (90)*	1.85 (0.5)*	67.83 (7.6)*	25.78 (5.6)*	6.39 (4.1)*	28.72 (5.5)*	26.02 (2.8)*	4.10 (1.3)*	714.24 (1.2)**	Sandy Loam
0.1-0.2	1,620 (80)	2.1 (0.7)	68.28 (7.3)	25.67 (7.6)	6.05 (3.6)	28.19 (5.9)	25.59 (1.7)	7.18 (1.7)	574.81 (1.3)	Sandy Loam
0.2-0.35	1,630 (90)	2.53 (0.9)	68.06 (6.1)	26.83 (6.2)	5.11 (3.4)	21.79 (4.3)	25.48 (2.4)	7.94 (1.5)	693.58 (1.5)	Sandy Loam
0.35-0.5	1,670 (60)	2.06 (1.1)	68.11 (6.6)	24.28 (6.4)	7.61 (3.8)	23.37 (2.6)	25.10 (2.1)	9.91 (2.1)	592.70 (1.5)	Sandy Loam

* Standard deviations are reported in the parentheses (n=18 samples for each depth or layer)
**Values in the parentheses are geometric standard deviations.

The infiltration rate was measured at 0.05 m and 0.15 m of soil depth using double ring infiltrometer according to ASTM D3385–03 standard test method and DIN 19682-7 (1997). The aim of using the double ring infiltrometer is to limit the lateral spread of water after penetration. It consisted of a pair of steel infiltration rings with 0.28/0.53 m diameters. The height of the rings was 0.25 m, and they have one cutting edge. The rings were inserted into the soil partially (0.05 m) and filled with water. After that, we recorded the water depth and corresponding time of its infiltration in the soil.

Plant height, above-ground biomass, leaf area index, and green canopy cover measurements

These parameters were monitored throughout the growing season. During the experiment, the heights of plants were measured at regular ten days intervals from 15 days after sowing to maturity. The plant height was measured using a measuring tape from the soil surface to the highest point of the arch of the uppermost leaf whose tip is pointing down. For this purpose, three randomly selected plants in the middle rows of each plot were tagged. Three plants per plot were randomly selected, clipped at the soil surface, then sun-dried until a constant weight was observed to measure the biomass. This occurred at 20 days intervals from 15 days after sowing to maturity. The biomass included grain and stover. For LAI, the area of each of the fresh leaves of the tagged plants was determined using a non-destructive method. First, the leaf area was calculated by multiplying the manually measured length and maximal width of each leaf with a shape factor k, empirically determined to be 0.75 for maize, by the plant density (Lizaso et al., 2003) (Equation 5).

$$LA = L \times W \times 0.75 \quad (5)$$

Where LA represents leaf area, L is leaf length, W stands for the maximum leaf width, and 0.75 is the coefficient used for maize (Yi et al., 2010). Then, the LAI was determined using Equation 6.

$$LAI = \frac{leaf\ area(m^2 plant^{-1}) \times 70{,}000(plantha^{-1})}{10{,}000(m^2 ha^{-1})} \quad (6)$$

The CC was obtained from the LAI by using the following formula (Hsiao et al., 2009).

$$CC = 1.005 \times [1 - exp(-0.6 \times LAI)]^{1.2} \quad (7)$$

The growth of the maize crop is strongly related to the accumulation of the daily temperature known as Growing Degree Day (GDD). Its cumulative form is commonly expressed as (Djaman et al., 2013):

$$GDD = \sum_{i=1}^{n} \left[\frac{(T_{max} + T_{min})}{2} - T_{base}\right] \quad (8)$$

Where T_{max} is maximum air temperature, T_{min} is minimum air temperature, T_{base} is the base temperature threshold (below which crop development does not progress), and n is the number of days. In this study, the base temperature and the maximum temperature thresholds used are 10 °C and 30 °C, respectively. This means, for instance, when the temperature values exceed the upper limit, they were reset equal to 30 °C (Djaman et al., 2013).

Maize yield and Water Use Efficiency (WUE)

At the end of the growing period, maize grain yield was harvested at physiological maturity from all plots. The harvest area of 12 m^2 (4 m x 3 m), including the four middle rows, was considered for the yield quantification. The harvest was executed by hand when all leaves were dry. Then, the maize grains were separated from the cobs and sun-dried until a constant weight was observed (at 12–14% moisture content). Water Use Efficiency (WUE), yield per unit water consumed, was also evaluated for all the irrigation treatments.

The Harvest Index (HI) was calculated by dividing the grain yield by the above-ground biomass after adjusting for moisture content. The Deficit Irrigation Stress Index (DISI) of the crop yield was calculated as follows (Pandey et al., 1984):

$$DISI = \frac{(Yield\ of\ unstressed\ treatment - Yield\ of\ stressed\ treatment)}{Yield\ of\ unstressed\ treatment} \times 100 \quad (9)$$

The DISI of the other crop growth parameters was computed similarly.

Statistical analyses

The comparison of the above-ground biomass, LAI, CC, plant height and grain yield among treatments were performed by an Analysis of Variance (ANOVA). The Shapiro-Wilk (Shapiro and Wilk, 1965) test was applied to determine if the measured quantities were normally distributed. The PROC ANOVA in Statistical Analytical System (SAS) (SAS Institute Inc, 2015) was used to run the analysis of variance. The treatment means were separated using Tukey's Honestly Significant Difference (HSD) at 5% significance level.

Effects of irrigation regimes and plant densities on the dry grain yield and dry above-ground biomass

The crop data collected during the experiment was used to calibrate AquaCrop in order to simulate the effects of different irrigation regimes and plant densities on the grain yield and biomass. There are two plant densities recommended by extension agents in the study area: (i) 0.8 m distance between rows and 0.35 m between two plants on a row, which gives 70,000 plants per hectare (Pd1); and (ii) 0.8 m distance between rows and 0.4 m between two plant on a row, which gives 62,500 plants per hectare (Pd2). These two plant densities were considered in the analysis. Following the field experiment, three irrigation regimes (Ir1, Ir2 and Ir3) were distinguished by withholding water at specific growth stages (Table 3).

TABLE 3
Seasonal irrigation applied to maize at different crop growth stages based on the crop evapotranspiration in northern Togo

Week	Crop stage	Irrigation regime		
		Ir1	Ir2	Ir3
1	VE*	28	28	28
2	V1	30	30	30
3	V3	31	–	–
4	V5	44	44	44
5	V7	42	–	–
6	V9	55	55	55
7	V11	50	–	–
8	V13	77	77	77
9	V15	70	70	70
10	VT	61	–	–
11	R1	44	44	44
12	R2	55	55	–
13	R3	61	61	61
14	R4	33	33	–
15	R5	41	41	41
16	R6	34	34	–
Seasonal irrigation (mm)		756	572	450
		FI	80% FI	60% FI

*VE = emergence; V1 ¬– V15 = appearance of Leaf 1 to appearance of Leaf 15; VT = tasseling; R1 = silking; R2 = blister; R3 = milk; R4 = dough; R5 = dent; R6 = physiological maturity (Pandey et al., 2000b); FI = Full Irrigation. The combination the irrigation regimes and plant densities gave six scenarios Pd1-Ir1, Pd1-Ir2, Pd1-Ir3, Pd2-Ir1, Pd2-Ir2, and Pd2-Ir3, which were evaluated using the AquaCrop version 5.0. Also, these scenarios were assessed using the irrigation optimiser GET-OPTIS to improve the outputs.

RESULTS

Weather conditions

Figure 3 shows the daily rainfall, air temperature, and reference evapotranspiration, relative humidity, wind speed, and sunshine throughout the experiment. The average daily maximum and minimum air temperatures were 36 °C and 23 °C, respectively (Figure 3a). The daily maximum, as well as minimum temperatures, were relatively low from mid-December 2017 to the end of January 2018. Both maximum and minimum temperatures reached their highest level in March 2018, 40.5 °C and 29.5 °C, respectively (Figure 3a). During the growing season, rainfall occurred only on 23 February (15.5 mm) and 21 March (9.5 mm), 2018. The daily reference evaporation, from mid-December 2017 to mid-February 2018, fluctuated between 6 and 10.5 mm/day, while from mid-February to end of March 2018 it ranged from 2.5 to 8 mm/day (Figure 3a).

The daily maximum and minimum relative humidities, from mid-December 2017 to mid-January 2018, fluctuated around 40% and 20%, respectively. From mid-February to the end of March 2018, they reached 80% and 40%, respectively (Figure 3b). The lowest level of daily wind speed was observed from mid-February to the end of March 2018 (Figure 3c). Throughout the growing season, the sunshine duration fluctuated around 8 hours/day. The lowest values of sunshine duration were recorded towards the end of the growing season (i.e., 1–4.8 hours/day) (Figure 3d).

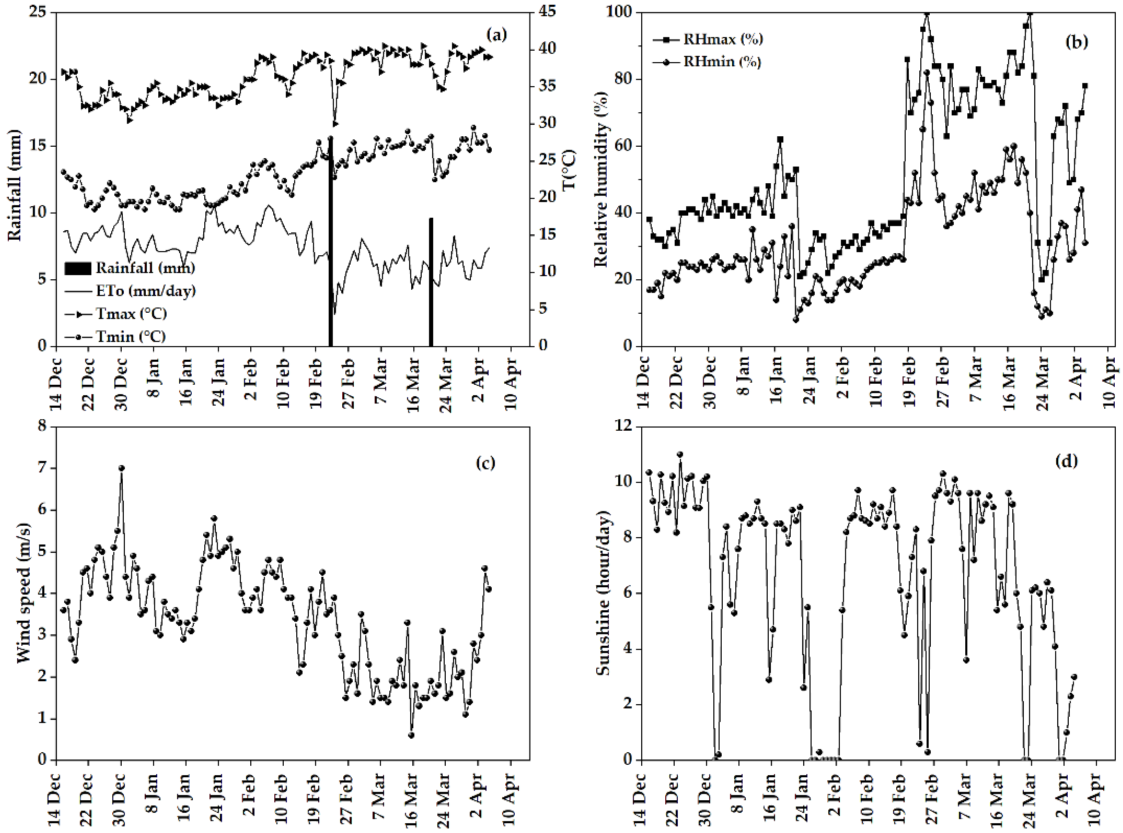

Figure 3

Daily (a) rainfall, air temperature, and reference evapotranspiration; (b) relative humidity; (c) wind speed; and (d) sunshine duration, of Dapaong climate station located 5 km away from the experimental site

Soil infiltration during the experiment

The infiltration results are shown in Figure 4. Infiltration rates at 0.15 m soil depth were greater than the infiltration rates at 0.05 m depth soil depth at the beginning of the measurements. For instance, during the first five minutes, the infiltration rate at 0.15 m soil depth was 0.6 m/hr whereas the rate at 0.05 m soil depth was 0.3 m/hr (Figure 4). However, the infiltration rates tend to be constant and similar for both soil depths after 200 minutes of continuous measurement.

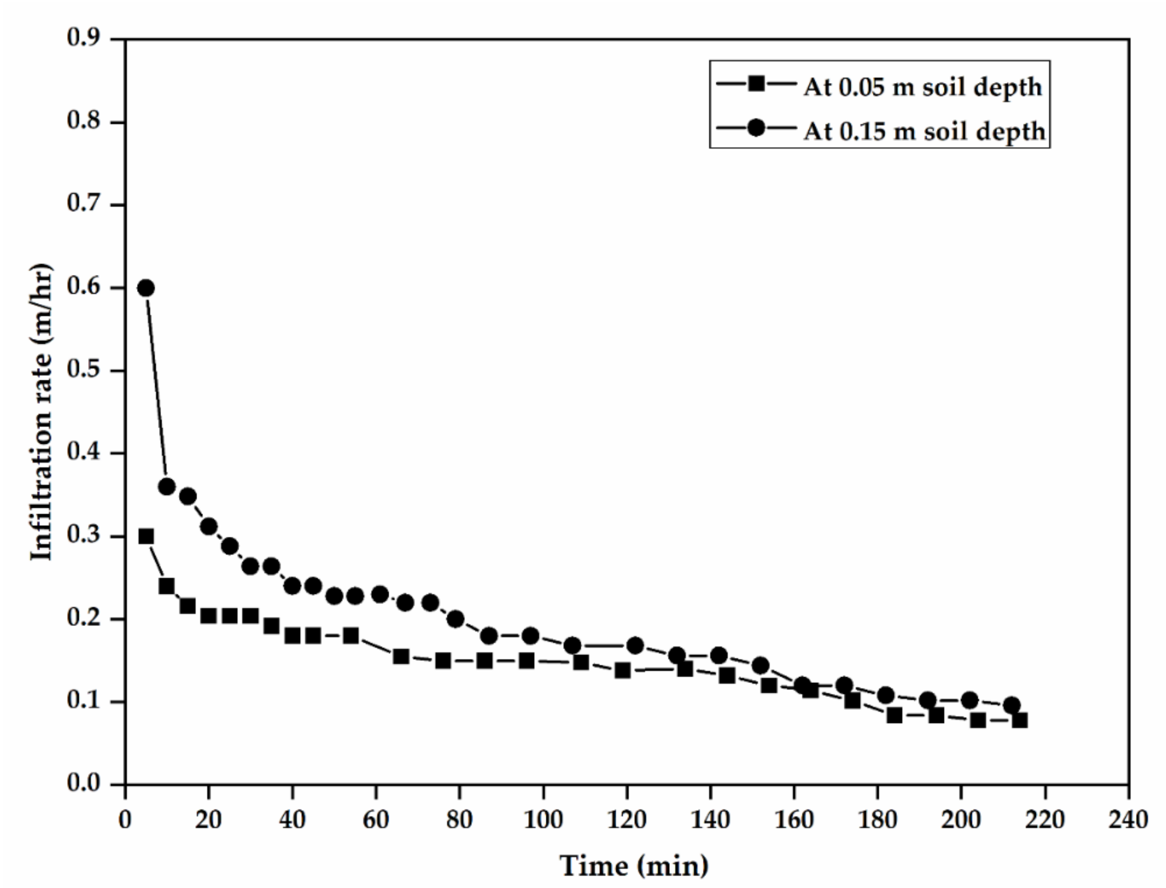

Figure 4
Infiltration rate of the soil of the experiment site

Effect of irrigation levels on plant height, above-ground biomass, leaf area index, green canopy cover, grain yield, and water use efficiency

Figure 5 shows the daily maize crop evapotranspiration and the cumulative GDD during the experiment period. The daily maize crop evapotranspiration ranged from 2.9 to 12.7 mm/day with the highest being recorded in February 2018 (50–70 Days After Planting (DAP)) (Figure 5a). This period is part of the mid-season growth stage of the maize crop during the experiment. Also known as thermal units (TU), the cumulative GDD from emergence to harvest was 1,845 °C (Figure 5b).

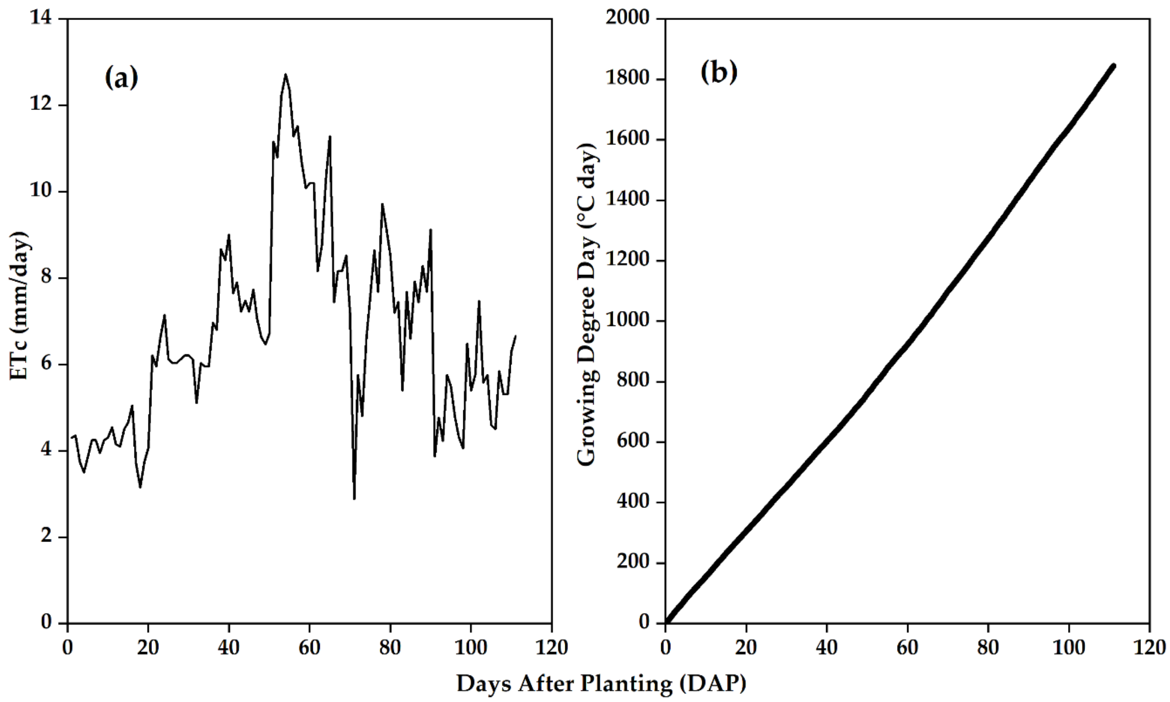

Figure 5
(a) Crop evapotranspiration; and (b) Cumulative growing degree days during the experiment period

The crop evapotranspiration and the volume of irrigation water applied throughout the experiment for the three treatments are presented in Table 4. The maize crop FI water applied in the dry season in northern Togo was 1,038.5 mm (Table 4). From sowing (16 December 2017), it took 111 days to reach maturity (5 April 2018) which was when the plants dried up on the field. With deficit irrigation, 40% less water is applied (i.e., 632.6 mm vs. 1,038.5 mm). For all the three treatments, the total volume of water applied during the mid-season stage was greater than the amount of water used in the other growth stages. The total crop evapotranspiration computed from sowing to harvest using the meteorological station weather data as well as the adjected crop coefficients was 755.2 mm. This value is higher than the crop evapotranspiration obtained from AquaCrop (< 730 mm) when simulating the experiment with the data collected from the field (Table 4).

TABLE 4
Crop evapotranspiration and depth of water applied in the growth stages

Growth stages	Period (days)	Volume of water applied (mm)			ET_c (mm) (weather data)
		FI	80% FI	60% FI	
Initial	20	193.8	155.3	137.8	82.4
Development	30	280.2	224.3	157.3	203.7
Mid-season	46	507	405.5	303.5	385.8
Late-season	15	57.5	46	34	83.3
Total	111	1,038.5	831.1	632.6	755.2
ET_c (mm) obtained from AquaCrop		730	721	710	–

FI = Full Irrigation; ET_c= Crop Evapotranspiration

The biomass, LAI, CC, and plant height during the experiment are depicted in Figure 6. The biomass increased rapidly during the development and mid-season stages, peaked and then declined, indicating the beginning of leaf senescence, under all the three treatments. The 80% FI induced a later peak and a subsequent decline in the biomass at the end of the mid-season stage than the other treatments (Figure 6a). Also, the values of the biomass at emergence were statistically similar ($p > 0.05$) under the FI, 80% FI and 60% FI. However, in the late season stage, the differences in the biomass were significant ($p < 0.05$) between the FI and 60% FI (Figure 6a). The plants in the 60% FI had the lowest LAI and CC, while the greatest values of these parameters were recorded on the fully irrigated plants. From the emergence, under the FI, 80% FI and 60% FI, the CC and the LAI increased rapidly during the development and mid-season stages, peaked at mid-season stage (≈ 75 DAP, cumulative TU = 1,185°C) and then declined indicating leaf senescence (Figure 6b,c). Similarly, under the FI, 80% FI and 60% FI, the plant height increased quickly during the development and mid-season stages, peaking at the end of the mid-season stage (≈ 85 DAP, cumulative TU = 1,368 °C). From then on, the plant height seemed to be constant until the harvest under the three treatments (Figure 6d). Maximum plant height varied from 1.33 m (60% FI) to 2.12 m (FI).

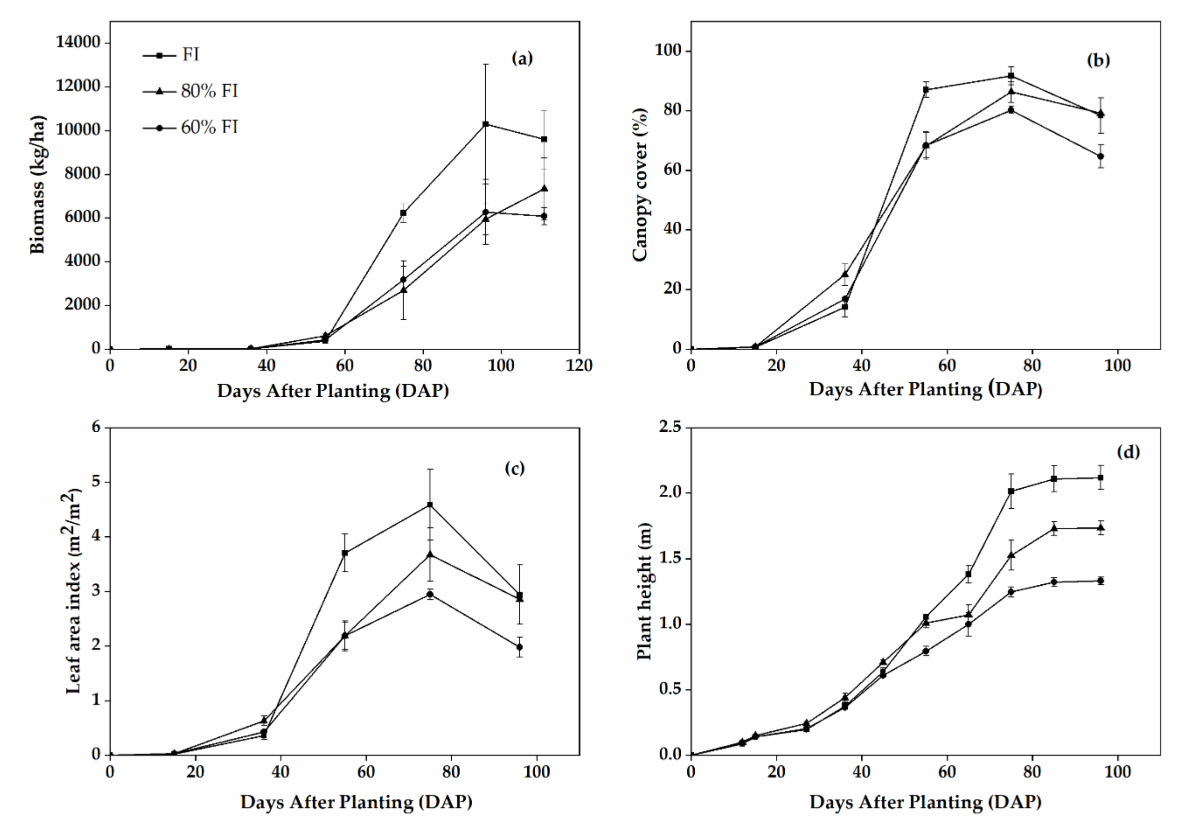

Figure 6
(a) Measured above-ground biomass; (b) canopy cover; (c) leaf area index; and (d) plant height for the three treatments during the experiment period. Vertical bars indicate standard deviations ($n = 9$)

Figure 7 shows the average measured maize grain yield and WUE of the three treatments at the end of the experiment. The FI had the greatest grain yield (2,200.4 kg/ha), while the lowest grain yield was recorded under the 60% FI (1,068.3 kg/ha) (Figure 7). Also, the grain yield differences between FI and 60% FI were significant ($p < 0.05$). Nevertheless, the grain yield differences between FI and 80% FI were not significant ($p > 0.05$). The 80% FI had WUE (0.22 kg/m^3) similar to that of FI (0.21 kg/m^3). The highest variability in the grain yield was observed under 60% FI (Figure 7).

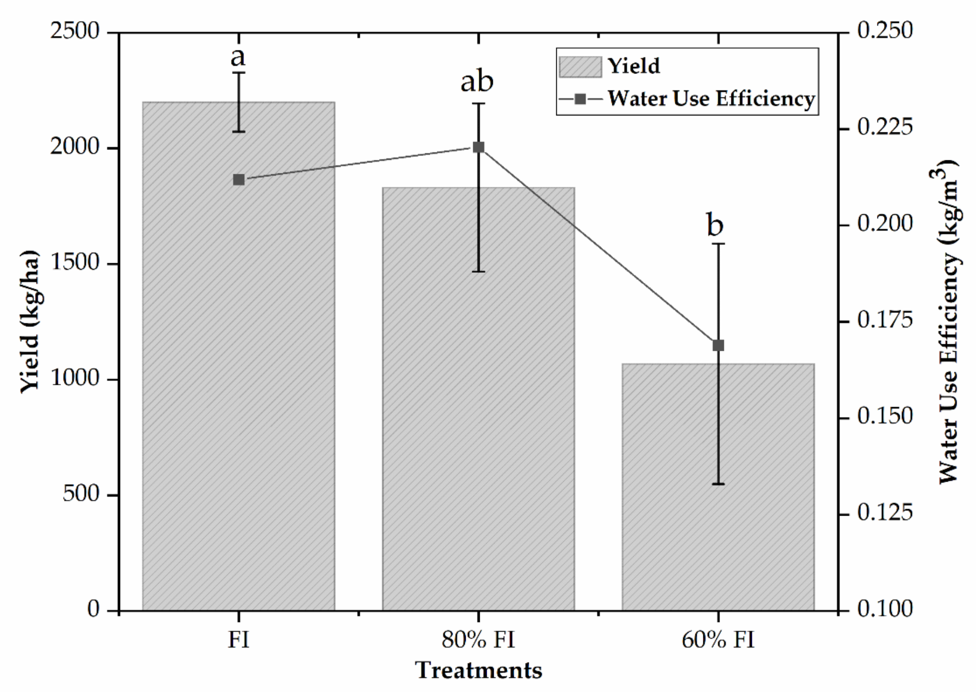

Figure 7
Measured maize grain yield and the corresponding water use efficiency for the three treatments. Different letters represent significant differences ($p < 0.05$). Vertical bars indicate standard deviations ($n = 3$)

Evaluation of harvest index and deficit irrigation stress index of maize grain yield and crop growth parameters

The maize yield HI and DISI are presented in Table 5. The maize crop harvest index ranged between 24.61 (60% FI) and 26.08 (FI) with an average of 25.37 (Table 5). The DISI for the grain yield under 60% FI was approximately three times greater than that of 80% FI (Table 5). Thus, the maize grain yield under 60% FI experienced more water-related stress than that of the other treatments.

TABLE 5
Harvest index and deficit irrigation stress index of the measured yield for the three irrigation treatments

Treatment	HI (%)	DISI (%)
FI	26.08	0.00
80% FI	25.41	16.79
60% FI	24.61	51.45
Mean	25.37	–

FI = Full Irrigation; HI = Harvest Index; DISI = Deficit Irrigation Stress Index

The results in Table 6 illustrate the mean biomass, CC, LAI, and plant height and the corresponding DISI of FI, 80% FI, and 60% FI for all the maize crop growth stages. The biomass, CC, LAI, and plant height differences among FI, 80% FI and 60% FI were not significant ($p > 0.05$) for all the crop growth stages except the biomass during the late-season stage (Table 6). Considering the fully irrigated maize as a reference treatment, the maize crops under 80% FI and 60% FI did not experience any stress due to lack of water supply during the initial and development stages. However, the plants under 80% FI and 60% FI were subject to stresses related to a shortage of water supply during the mid-season and late-season stages (Table 6). Mainly, these stresses were more pronounced for 60% FI than 80% FI. For instance, the DISI for LAI and plant height under 80 % FI (60% FI) were 29.38 (38.07) and 18.66 (33.5), respectively, during the mid-season stage. Similarly, the DISI for biomass under 60% FI was approximately 40 times greater than that under 80% FI during the late-season stage (Table 6).

TABLE 6
Mean above-ground biomass, canopy cover, leaf area index, and plant height and the corresponding deficit irrigation stress index of FI, 80% FI and 60% FI for all the maize crop growth stages

Treatment	Initial stage		Development stage		Mid-season stage		Late season stage	
	Mean value of the parameter	DISI (%)	Value of the parameter	DISI (%)	Value of the parameter	DISI (%)	Value of the parameter	DISI (%)
Above-ground biomass (kg/ha)								
FI	10	0.00	370	0.00	8,260	0.00	7,190b	0.00
80% FI	10	0.00	610	-62.50	4,320	47.74	7,170b	0.27
60% FI	10	0.00	420	-12.50	4,730	42.80	3,960a	44.98
Mean	10	–	470	–	5,770	–	6,110	–
Canopy Cover (%)								
FI	0.66	0.00	14.16	0.00	89.39	0.00	78.32	0.00
80% FI	0.75	-14.67	25.03	-76.82	77.26	13.57	79.17	-1.09
60% FI	0.79	-20.95	16.86	-19.08	74.31	16.87	64.61	17.50
Mean	0.73	–	18.68	–	80.32	–	74.03	–
Leaf Area Index (m^2/m^2)								
FI	0.03	0.00	0.36	0.00	4.15	0.00	2.94	0.00
80% FI	0.03	0.00	0.63	-73.91	2.93	29.38	2.86	2.89
60% FI	0.03	0.00	0.43	-17.63	2.57	38.07	1.98	32.64
Mean	0.03	–	0.47	–	3.21	–	2.59	–
Plant height (m)								
FI	0.11	0.00	0.40	0.00	1.64	0.00	2.12	0.00
80% FI	0.13	-10.29	0.46	-15.01	1.33	18.66	1.73	18.17
60% FI	0.12	-4.41	0.39	2.48	1.09	33.50	1.33	37.21
Mean	0.12	–	0.42	–	1.35	–	1.73	–

Means within the same column not followed by letters or followed by the same letter are not significantly different at 5% level; FI = Full Irrigation; DIDSI = Deficit Irrigation Stress Index.

Effects of irrigation regimes and plant densities on the dry grain yield and dry above-ground biomass

The dry grain yield, as well as the final dry above-ground biomass, were linearly affected by deficit irrigation at all plant density (Table 7). Deficit irrigation was created by withholding water at different maize growth stages. When four irrigations were withheld (Ir2) at V3, V7, V11 and VT (vegetative phases), 29.3% and 29.7% reductions in the grain yield and final biomass occurred at all plant densities, respectively. When deficit irrigation was imposed during the reproductive phases in addition to the vegetative growth stages (Ir3), grain yield and final biomass reductions of up to 54% and 48%, respectively, were observed at all plant densities. Yield, as well as biomass, decreased slightly when the plant density reduced (Pd2) for all irrigation regimes assessed. Generally, WUE had not increased when irrigation was withheld during vegetative and reproductive stages (Ir2 and Ir3) compared to fully irrigated treatment (Ir1). However, a moderate level of deficit irrigation during vegetative growth stages (Ir2) could result in similar WUE values to that of fully irrigated treatment. Also, the results showed that the optimisation of all the irrigation regimes by applying GET-OPTIS has contributed to improving the dry grain yield and at the same time using less water as compared to the scenarios without optimisation. This is supported by the increase in the WUE for all the optimised scenarios.

TABLE 7
Dry grain yield, dry final above-ground biomass and Water Use Efficiency as affected by irrigation and plant density at different growth stages in northern Togo

Irrigation regime and plant density scenarios	Crop characteristics (without irrigation optimisation)			Crop characteristics (with irrigation optimisation)	
	Dry grain yield (kg/ha)	Dry final above-ground biomass (kg/ha)	Water Use Efficiency (kg/m^3)	Dry grain yield (kg/ha)	Water Use Efficiency (kg/m^3)
Pd1-Ir1*	2,593	9,974	0.34	2,612	0.42
Pd1-Ir2	1,834	7,006	0.31	2,440	0.46
Pd1-Ir3	1,195	5,242	0.27	2,215	0.52
Pd2-Ir1	2,577	9,911	0.34	2,601	0.47
Pd2-Ir2	1,822	6,966	0.31	2,431	0.47
Pd2-Ir3	1,183	5,183	0.26	2,098	0.49

*Pd = Plant density; Ir = Irrigation regime

DISCUSSION

Maize crop responds differently to various volumes of irrigation water applied from the emergence to harvest. In this study, the biomass—including grain and stover at physiological maturity—and grain yield were significantly affected by the irrigation regimes. Regarding crop response to water performance, the 80% FI treatment was very similar to the fully irrigated treatment.

Lower temperatures in December and January caused differences in the reference and crop evapotranspirations between early and late growth stages. Although the temperatures were relatively low during the initial stage, they contributed to achieving seed germination and emergence rates of more than 90%. The fact that the biomass, LAI, and CC increased dramatically during the mid-season stage can be explained by the combined effect of higher temperatures and sufficient water supplied in this stage. Also, the wind speed was relatively high during the mid-season stage, inducing high crop evapotranspiration. A substantial amount of biomass was produced. Temperatures have no significant effect on maize crop growth during the late-season stage because senescence was reached and subsequently photosynthesis was reduced.

There were no significant differences ($p > 0.05$) in plant height, LAI, and CC between any of the treatments in all the growth stages because soil moisture might have been adequate for the plant growth. This similarity was evident by observing the various maize plots during the experiment, especially in the early growth stages. These results are in agreement with those of Djaman et al. (2013). The biomass in the late growth stages was markedly affected by irrigation regimes under our experimental conditions. Khaksar et al. (2013) reported that under severe water stress—which seems to be 60% FI of our experiment—stomata are closed inducing a decrease in carbon dioxide uptake, and subsequently this leads to a reduction of photosynthesis. During the experiment, the plants under 60% FI reacted to the severe water stress by wrapping their leaves in the daytime at the beginning of the stress (Figure 8). This result is in line with the findings of Worou and Saragoni (1988) who assessed maize yield response to water stress in the long dry season in southern Togo. It should be stressed that these authors did not use the same maize variety as in our experiment.

Figure 8
Appearance of maize plants under different irrigation treatments at 76 DAP (1 March 2018)

Crop yields are strictly linked to moisture availability, especially at crucial crop growth stages (Mutiro et al., 2006). These crucial growth stages for maize crop correspond to tasselling and silking (VT and R1) (Farré and Faci, 2009), which fell under the mid-season stage during our experiment for all treatments. Under deficit irrigation treatments, the plants reached tasselling-silking stages while experiencing water stress, resulting in differences in the grain yield compared to the fully irrigated plants. These differences in the grain yield were significant between 60% FI and fully irrigated plants because the water stress under the former was more pronounced. Our results are in agreement with those reported by Djaman et al. (2013) and Earl and Davis (2003). On average, the maize grain yields obtained under all the treatments are relatively low compared to the attainable potential yield reported in the literature: 3,500–5,000 kg/ha (Didjeira et al., 2007).

Nevertheless, the yields obtained at the end of our experiment for all treatments, 2,200.4 kg/ha (FI), 1,830.9 kg/ha (80% FI) and 1,068.3 kg/ha (60% FI) are greater than that of Worou and Saragoni (1988) which were 1,800 kg/ha, 900 kg/ha, and 300 kg/ha for no water stress, moderate water stress and severe water stress treatments, respectively. The Togolese Direction of Agricultural Statistics, Informatics, and Documentation, DSID (2017) reported 1,200 kg/ha as the long-term (2000–2016) average maize grain yield obtained by farmers under rainfed conditions in northern Togo. Similarly, the Global Yield Gap Atlas, GYGA (2015) reported 1,700 kg/ha, 1,800 kg/ha, 1,600 kg/ha, and 1,000 kg/ha as long-term average maize grain yields got by farmers under rainfed conditions in Ghana, Mali, Nigeria, and Niger, respectively. The reasons for obtaining a low level of maize yield during our experiment are threefold. Firstly, TZEE-W, the maize variety used for our experiment, is a local one. It is a short-cycle variety with a low level of yield potentials. Secondly, the plants during our experiment might have been subject to high temperature stress because TZEE-W is a rainy season variety—dry season temperatures are higher than that of the rainy season. By field observation during the experiment, it can be concluded that temperature stress was more pronounced in late vegetative growth stages (V15 and VT) and early reproductive stages (R1–R3). This finding was supported by the outputs of the simulation of the field experiment using AquaCrop. Lastly, fall armyworm (Spodoptera frugiperda), an insect pest, posed a serious threat to the plant development during our experiment. This damage might have affected the maize grain yield measured at the end of our experiment. Fall armyworm prefers maize to other crops such as sorghum, rice, millets, and soybean. Since fall armyworm is a recently introduced pest in sub-Saharan Africa (January 2016) (Nagoshi et al., 2017), proper control methods are limited. This insect pest has the potential to cause tremendous maize yield losses if proper care is not taken (FAO, 2018).

Regarding WUE, 80% FI was similar to the FIbecause it appears that the plants under the 80% FI received an optimal volume of irrigation water in the crucial growth stages. Thus, deficit irrigation may be used to boost WUE. Such results are expected because plants under FI are provided with more than the required volume of water for their growth. These results are corroborated by those of Pandey et al. (2000a) who assessed the effects of deficit irrigation on maize in a Sahelian environment. The rate of infiltration, which is subject to the rate of water supply controls how much water comes in the root zone and how much exits the field as runoff (Hillel, 1982). Since the soils have been ploughed up to 0.15–0.25 m depth each season annually for a long time in northern Togo, they are compacted below 0.35 m depth. Therefore, maize plants tend to develop more horizontal rooting system than a vertical one. During our experiment, on all the plots, the maximum rooting depths reached by the plants were less than 0.50 m. Also, the top-soils are poor in organic matter. In northern Togo, it appears that conservation agriculture is required to improve plant roots penetration and infiltration capacity. In the area, some farmers have started using cover plants (*Bracharia brizantha* and *Crotalaria spectabilis*) in association with cereal crops or between two growing seasons to loosen the soil. It is also worth highlighting the importance of irrigation (full and deficit) for improving maize yield in West Africa using crop modelling approach (Abdalhi and Jia, 2018).

CONCLUSIONS

A field experiment was carried out to assess the effect of full and limited irrigation management practices on maize biomass, LAI, CC, plant height and grain yield during the dry season (November 2017 to April 2018) in northern Togo, West Africa. The results of our study indicate clearly that the biomass—including grain and stover at physiological maturity—and grain yield were significantly ($p < 0.05$) affected by the irrigation regimes. Concerning crop response to water performance, the 80% FI was very comparable to the fully irrigated treatment. WUE for 80% FI was similar to that of FI for the field experiment as well as its simulation using AquaCrop model. Deficit irrigation during early vegetative growth stage reduced the biomass, LAI, CC, plant height, and grain yield modestly. In contrast, deficit irrigation during the mid-season stage (tasselling and silking) lessens the biomass severely at physiological maturity and final grain yield. Reductions in the plant density may result in a decline in the biomass and grain yield, while no change was observed in WUE. The optimisation of the irrigation regimes could contribute to improving the grain yield and the WUE, and at the same time, save water.

This study demonstrated that lowering irrigation during the early vegetative growth stage had less impact on biomass production than when deficit irrigation occurred during the mid-season (reproductive) stage. These reductions are a direct effect of diminished LAI. The adaptive strategy of maize under a moderate level of deficit irrigation appears to reduce the biomass and the grain yield while WUE could remain similar to that of FI in these experimental, soil and crop management, and climatic conditions. Dry season maize cultivation is a delicate practice. Its realisation is subject to water availability in the soil, especially during crucial crop growth stages. Furthermore, the framework used to simulate the irrigation schedules can be extended by adding a soil variability dimension to it. The assessment can also be made more comprehensive by taking into account farmers' socioeconomic characteristics.

When interpreting the results of this study, one should bear in mind that the results presented in this study are based on data collected during one growing season. The approach employed in this study consisted in simulating the irrigation schedules with a calibrated crop model and then implement them on the field. However, this study gives substantial insights into maize crop response to irrigation regimes because to date, no work has been published on similar topics in northern Togo. Thus, there is room for conducting further studies on the same topic in the area by repeating the experiment to capture more variabilities in the measured crop growth parameters and also by testing further dry-season adapted crops and crop varieties.

ACKNOWLEDGEMENTS

This study was supported by a grant to A.G.-T. PhD scholarship under the Merit Scholarship Programme (MSP) 2015/2016 of the Islamic Development Bank (IsDB). Also, this study was partially funded by the United Nations University Institute for Integrated Management of Material Fluxes and Resources (UNU-FLORES) and Technische Universität Dresden (TUD), Germany. The logistical assistance received from the UNU-FLORES, ITRA, and TUD is gratefully acknowledged.

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A.3 Impact of Climate and Soil Variability on Maize (*Zea mays L.*) Yield under Full and Deficit Irrigation in the Savannah Region of Northern Togo, West Africa

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Abstract:

In the situation of an increasing population in West Africa, frequent yield losses due to erratic rainfall, and degraded soils, the knowledge of the impact of climate and soil variability on maize (*Zea mays L.*) yield is needed to improve maize production in the region sustainably. Thus, full irrigation and controlled deficit irrigation management strategies under different soil and climate variability scenarios were investigated in this study. The impact of soil variability on maize yield was assessed by developing and applying a stochastic soil generator. Rosetta 3 and Saxton-Rawls pedotransfer functions were utilised to convert the synthetic basic soil data into hydraulic characteristics which served as inputs for the crop model. A field experiment was conducted on maize from December 2017 to April 2018 to validate the AquaCrop preliminary calibration for the study area. Also, the Optimal Climate Change Adaption Strategies in Irrigation framework (OCCASION), which considers climate variability, was adapted and applied. Overall, based on the values of the statistical indicators, AquaCrop has predicted well the canopy cover, above-ground biomass, and grain yield for all the irrigation treatments assessed. We found that the maximum expected maize yield ranged from 2.5 to 3 Mg ha^{-1} considering all the scenarios investigated in this study. Also, the full irrigation storage was reached between 350 mm and 500 mm when all scenarios assessed are considered. This suggests that climate variability may lead to high variability in the maize yields of northern Togo than soil variability does. The findings of this study indicate that the AquaCrop model could be used to simulate the maize yield with acceptable accuracy in data-scant regions like West Africa under diverse irrigation management strategies. Large- and small-scale water harvesting, access to groundwater, and irrigation infrastructures would be needed to implement the irrigation management strategies assessed in this study.

Keywords: AquaCrop, Maize, climate and soil variability, Irrigation, West Africa.

1. Introduction

Soil variability of a given crop field influences the hydraulic properties. In turn, soil water content at different crop growth stages has an impact on crop yield (Papiernik et al., 2005). Crop models have been used to assess the impact of soil variability on crop yields. Many studies which evaluated the impact of environmental factors on crop yield have failed to consider the variability of soil properties in the assessment (Kloss et al., 2012; Schütze et al., 2012). Moreover, one limitation of some crop models is a significant amount of input parameters required to run them (Kasampalis et al., 2018; Motha, 2011). Notably, the application of crop models has been limited by lack of field-specific soil hydraulic properties such as saturated hydraulic conductivity and soil water content at various matric potentials. Current methods of direct measurements of these soil properties are laborious, time-consuming and therefore expensive (Koekkoek and Booltink, 1996). To overcome these difficulties, researchers proposed equations expressing soil hydraulic properties from easily measured soil properties, e.g., texture and bulk density, and or organic matter content (Rawls et al., 1982). This indirect estimation of soil hydraulic properties was first coined pedotransfer function (PTF) by Bouma (1989).

Over the past few decades, many PTFs have been developed (Rawls et al., 1982; Saxton et al., 1986; Saxton and Rawls, 2006; Schaap et al., 2001; Tóth et al., 2015; Vereecken et al., 1989; Wösten et al., 1999; Zhang and Schaap, 2017). Concerning their prediction methods, these PTFs can be grouped into two types, mechanistic and empirical approaches (Patil and Singh, 2016). The mechanistic approaches relate a soil pore-size distribution model to water content at different soil water matric potentials, while the empirical approaches consist of developing relationships between the predictors and estimands. The latter can be divided into two groups: point PTFs and parametric PTFs (Pachepsky and van Genuchten, 2011). Point PTFs relate soil water contents at several soil water matric potentials to basic soil properties, while parametric PTFs relate model parameters to basic soil properties.

No PTF can be considered as generic with broad spatial applicability because of the variations in soil formation factors and pedogenesis (Tietje and Tapkenhinrichs, 1993). The Rosetta PTF (Schaap et al., 2001) is one of the parametric PTFs that can be found in the literature. Rosetta estimates water retention parameters in van Genuchten's (1980) (vG) equation and predicts saturated hydraulic conductivity (Ks) based on Mualem (1976) pore-size model. It is calibrated and validated with large multinational databases covering soil data from a wide range of soil types. The Rosetta PTF showed reasonable predictions in evaluation studies and good functional performance with different sets of input data in simulating soil moisture variations at many fields in the world (Gérard et al., 2004; Nemes et al., 2003). Furthermore, the use of neural network analyses combined with the bootstrap method allows Rosetta program to give uncertainty estimates of the simulated hydraulic parameters. Also, the hierarchical structure of the Rosetta PTF permits optimal use of available input data—prediction of the hydraulic properties with limited or more extended sets of input data (Patil and Singh, 2016).

Many studies from all over the world opted for the Rosetta PTF. For example, in southern Spain, Vanderlinden et al. (2005) used Rosetta to prepare soil water-holding capacity map. Gérard et al. (2004) employed the Rosetta PTF to simulate daily average values of the measured water content over four years in a field at Rhone, France. These authors concluded that Rosetta showed good predictive abilities. Rubio and Llorens (2004) reported that the Rosetta PTF is adequate for predicting water content at field capacity (FC), but underestimates water content at permanent wilting point (PWP). Salazar et al. (2008) reported that Rosetta-estimated Ks values could be used in the DRAINMOD field-scale hydrological model to simulate drainage outflows as accurately as laboratory-measured Ks values in coarse-textured soils. In another study, Alvarez-Acosta et al. (2012) pointed out that the Rosetta PTF is a tool that can be used to estimate Ks in the absence of measured data for the soil in Lamesa, Texas, USA. The Rosetta PTF is implemented in Hydrus 1D, 2D, and 3D applications (Šimůnek et al., 2012, 2016, 2008). Recently, Rosetta (Schaap et al., 2001, denoted as Rosetta 1) was recalibrated in a new version named Rosetta 3 (Zhang and Schaap, 2017). One thousand bootstrap replicas were utilised to calibrate Rosetta 3 compared to 46 or 100 in Rosetta 1. Several deficiencies of Rosetta 1—pressure head-dependent bias in estimated water contents, ignorance of the uncertainty in the fitted vG parameters that were used to calibrate the models, and provision of only univariate uncertainties for estimated parameters—were addressed in Rosetta 3(Zhang and Schaap, 2017).

After an extensive analysis of PTFs, Gijsman et al. (2002) concluded that the discrepancy between estimation methods for water retention parameters was so significant that it is hard to recommend on which method to use for which soil. Nonetheless, Gijsman et al. (2002) found that Saxton method (Saxton and Rawls, 2006) produced the best results out of 8 PTFs with minimum root mean square error compared to field measured data for certain soil types in the United States. Saxton and Rawls (2006) used the USDA soil database to develop PTFs so that the soil hydraulic properties can be estimated only by texture and organic matter content. Therefore, there may be regions where the functions may not perform well (Han et al., 2015).

The West African region has been described as one of the most sensitive regions to the impacts of climate variabilities and change because of its dependence on rainfed agriculture (Kotir, 2011). Also, there is a change in the seasonal distribution and intensity of rainfall as well as an increase in the temperature in the area (Lobell and Gourdji, 2012). In northern Togo, a West African country, the rainy season, which covered six months in the 1970s, has decreased to five or four months nowadays (MERF, 2009). The Togolese agriculture which accounts for 38% of its gross domestic product, provides over 20% of the export revenue, and employs 70% of the active population, is predominantly rainfed (Bolor, 2010; Jalloh et al., 2013). Several crop simulation models have been used to assess the impact of climate variability and change on crop yield. These models include CropWat (Smith, 1992), AquaCrop (Hsiao et al., 2009; Raes et al., 2009; Steduto et al., 2009), DAISY (Hansen et al., 1990), PILOTE (Mailhol et al., 1997), APSIM (Keating et al., 2003), and DSSAT (Jones et al., 2003). Most of these models demonstrate considerable complexities and require a large amount of data to run (Iqbal et al., 2014). However, the AquaCrop model requires relatively few explicit and mostly intuitive parameters and input variables, necessitating simple methods for their derivation (Vanuytrecht et al., 2014).

A broad range of soil data is needed to assess the impact of soil variability on crop yields. There is a need for developing computer programmes to generate reliable soil basic properties data which, in turn, are used to evaluate the impact of soil variability on crop yield. Therefore, this paper aims at: (i) developing a stochastic soil generator for representing soil variability (basic properties) of a specific site and applying the generated data to Rosetta 3 and Saxton-Rawls pedotransfer functions to get soil hydraulic properties of northern Togo; (ii) analysing the performance of AquaCrop for maize under different irrigation management strategies; and (iii) evaluating the impact of soil and climate variability on maize (staple food) yield in northern Togo.

2. Materials and methods

2.1. Study area

The study was conducted in Northern Togo, at ITRA (Institut Togolais de Recherche Agronomique) research institute (10°52'49.13" N, 0°11'31.90" E, 295 m above sea level). Northern Togo falls under the Southern-Guinea-Savannah agro-ecological zone and is characterised by a single wet season a year (Ali, 2017; MERF, 2009). The growing season in the area ranges from May to October, while the dry season lasts from November to April. The annual rainfall varies from 900 to 1,100 mm, whereas the average annual temperature is 28°C

(Jalloh et al., 2013). Detailed descriptions of the study area are presented in (Gadédjisso-Tossou et al., 2018).

2.2. Development of the soil texture generator

The soil generator is implemented using the MATLAB Source Codes (Burkardt, 2018; Sandrock, 2018). It consists of three input parameters. First, *n* which represents the number of randomly generated soil samples. Second, *seed* which is a random parameter for the random number generator. Finally, *P* which stands for a vector with coordinates of the "sub-triangle" where the x-coordinates of the vertices of the triangle are in the first line and y-coordinates in the second line. The function adapted for this study is as follows.

Algorithm 1: random soil sample

```
function [ X, seed] = triangle_sample (n, seed, P)
    for j = 1: n
      [ e, seed] = r8vec_uniform_01 (m, seed);
      e_a = 1.0 - sqrt (e(m));
      e_b = (1.0 - e(1))* sqrt ( e(m) );
      e_c = e(1)* sqrt ( e(m) );
      X (1: m, j) = e_a.*P(: , 1)+e_b.*P(:,2) + e_c.*P(: , 3);
    end
retun
end
```

The most important output parameter is X, which store the randomly generated soil samples with x-coordinates of the dots in the sub-triangle in the first line and y-coordinates in the second line. When the shape of the soil class is a triangle, the following algorithm should be employed to run the random soil generator.

Algorithm 2: random soil sample – triangle

```
%% Definition of sub-triangle (an example)
Sand = [ 10 20 10]';
```

```
Silt = [5 10 15]';
Clay = [85 70 75]';
%% Conversion into triangular coordinate system
P = soil_triangle2cart (sand, clay, silt);
%% Sampling
[ X, seed] = triangle_sample (1000, 128884, P');
%% Conversion into triangular coordinate system
[m_sand, m_silt, m_clay] = cart2soil_triangle(X);
```

In case the shape of the soil class has more than three straight sides and angles, the following algorithm should be used for the sample generation.

Algorithm 3: random soil sample – polygon

```
function [ X, seed] = polygon_sample (n, seed, P)
retun
end
```

In this study, the soil generator was implemented for the United States Department of Agriculture (USDA) soil texture classification system. The data about the coordinates of the vertices of the classes were retrieved from Moeys (2018). Also, we assume that for a given site, samples of soil texture are uniformly distributed within a chosen class.

2.3. Estimation of Soil hydraulic parameters

The estimation of soil hydraulic properties begins with input data, which are either soil information from laboratory measurement (e.g., sand, silt, and clay) for a limited number of samples or soil class information (e.g., sandy loam class of USDA textural triangle) (Fig. 1). In the next step, these data will be fed into the soil texture generator to generate a large number of synthetic soil samples. The output of the soil texture generator will be fed, in turn, into PTFs such as Rosetta 3 (Zhang and Schaap, 2017) and Saxton and Rawls (2006). The output of the PTF will be hydraulic parameters, which are then used to compute the soil hydraulic properties required to run AquaCrop model namely the soil water content at saturation, field capacity (−33 kPa), and permanent wilting point (−1500 kPa) and saturated hydraulic conductivity.

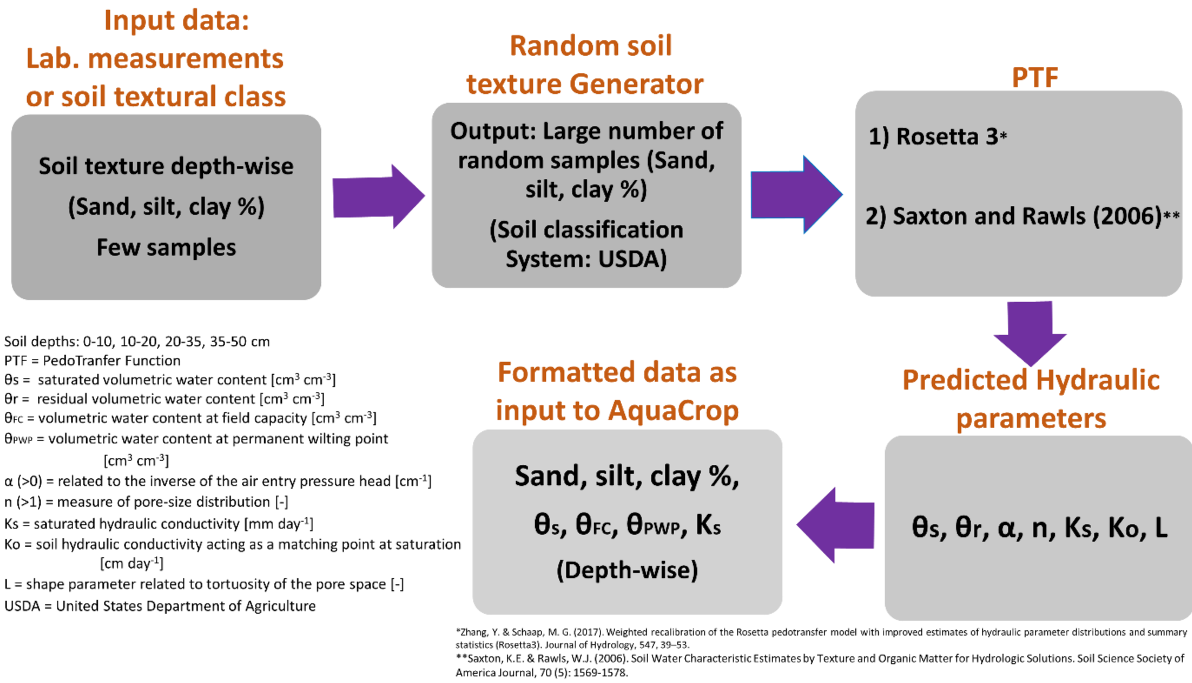

Fig. 1. Flowchart for estimating soil hydraulic parameters using pedotransfer functions (PTFs).

2.4. AquaCrop simulation model

2.4.1 Model background

AquaCrop, a water-driven crop simulation model, was developed by the Food and Agriculture Organization of the United Nations (FAO) (Steduto et al., 2012). Detailed descriptions of the model are presented in Raes et al. (2009), Steduto et al. (2009), and Hsiao et al. (2009). AquaCrop model simulates potential yields of major herbaceous crops as a function of water consumption under rainfed, supplemental, deficit, and full irrigation conditions (Steduto et al., 2012). In AquaCrop transpiration is translated into biomass using conservative crop parameters. The ratio of the biomass to transpiration is the normalised Water Productivity. The biomass is normalised for atmospheric evaporative demand and the air CO_2 concentration (Eq. (1)) (Steduto et al., 2012).

$$B_n = WP * \times \sum_{i=1}^{n} \left(\frac{Tr_i}{ET_{0i}}\right) \tag{1}$$

Where B_n is the cumulative above-ground biomass production after n days (g m^{-2}); and WP* is the normalised crop water productivity; Tr_i is the daily crop transpiration (mm day^{-1}); ET_{0i}

is the daily reference evapotranspiration (mm day^{-1}); i is the sequential days of the crop cycle (from 1 to n).

The crop yield is computed by multiplying the final biomass by a harvest index (HI) (Steduto et al., 2012). The model uses green canopy cover (CC) instead of leaf area index (LAI) as the basis for calculating transpiration and for separating soil evaporation from transpiration. AquaCrop, which was designed for a broad range of end-users, is also used as research tools to assess the environmental impact on crop growth and development (Steduto et al., 2009).

2.4.2. Parameters and input data

Like other crop models, AquaCrop consists of a soil–crop–atmosphere continuum. The climate component consists of daily data of maximum and minimum temperature, rainfall, ET0, and CO2 concentration. The FAO Penman-Monteith equation was used to compute the daily ET0. These data were collected at Dapaong Meteorological Station (Latitude: 10°51′44.10″ N, Longitude: 0°12′27.43″ E, Altitude: 330 m above sea level). The data ranges from December 2017 to April 2018 (field experiment)—detailed analysis of these data is presented in Gadédjisso-Tossou et al. (2019). Also, the 29 years (1983–2011) of weather data collected from the same meteorological station was used to generate 100-year synthetic weather data in order to assess the impact of climate variability on maize crop. The Long Ashton Research Station Weather Generator version 6.0 (LARS-WG) (Rothamsted Research, 2018) was used under the baseline (1961–1990) climate scenario, HadCM3, RCP4.5 (Thomson et al., 2011) and RCP8.5 (Riahi et al., 2011) for the study area. The detailed results of the calibration and validation of LARS-WG for the climate of northern Togo are presented in Gadédjisso-Tossou et al. (2018).

The crop input component of AquaCrop comprises both conservative and crop-specific parameters. The conservative parameters do not change with the cultivar. The crop-specific parameters used in this study were derived from the crop data collected during the field experiment mentioned above. These parameters include information about sowing, canopy cover, canopy senescence, flowering, rooting depth, soil management, and the maize cultivar. Detailed information about the experimental design and the analysis of the collected data are presented in Gadédjisso-Tossou et al. (2019).

The soil profile file in AquaCrop necessitates the soil texture data. It also requires the basic soil hydraulic properties such as saturated hydraulic conductivity, water content at saturation, field capacity, and permanent wilting point of the different soil profile depths (Table 1). The integral suspension pressure method (ISP) (Durner et al., 2017) was used to analyse the particle size distribution. The experimental determination of soil texture was done in the laboratory by a combination of sieving (sand) and gravitational sedimentation (silt and clay). The particle size distribution analysis was performed by following the German standard DIN ISO 11277 2002-08 (DIN, 2002). To measure the soil hydraulic properties, the ku-pF apparatus DT 04-01 was used. The procedure is based on Schindler (1980) measurement method. The van Genuchten (1980) equation—the best goodness of fit for the measured data—was used to get the soil hydraulic properties from the measured data with ku-pF apparatus. The soil electrical conductivity was measured per the German standard DIN ISO 11265:1997-06 (DIN, 1997). For each soil depth, 27 samples were analysed for the particle size distribution and 9 for the hydraulic properties and soil electrical conductivity. The arithmetic mean was used to get the representative value for each soil layer for all parameters except the saturated hydraulic conductivity for which we used geometric mean (Oosterbaan and Nijland, 1994). Detailed information on soil sampling is given in Gadédjisso-Tossou et al. (2019). The soil characteristics are presented in Table 1.

Table 1. Soil particle size distribution, initial soil water content (SWC), saturated water contents (θ_s), field capacity (θ_{FC}), and permanent wilting point (θ_{PWP}), electrical conductivity (EC) and saturated hydraulic conductivity (K_s) for the experiments at different soil profile depths.

Soil Depth	**Particle size distribution***			**Initial Soil water content**	θ_s	θ_{FC}	θ_{PWP}	K_s	**Electrical conductivity (EC)**	**Textural Class**
	Sand	Silt	Clay							
m		% (w/w)			% (v/v)			mm day^{-1}	dS m^{-1}	
0–0.1	71.44	22.44	6.12	28.72	34.87	26.02	4.10	714.24	0.039	Sandy loam
	(8.8)	(7.4)	(3.6)	(5.5)	(1.8)	(2.8)	(1.3)	(1.2)	(0.005)	
0.1–0.2	70.26	23.15	6.59	28.19	36.51	25.59	7.18	574.81	0.026	Sandy loam
	(6.8)	(7.2)	(3.3)	(5.9)	(1.6)	(1.7)	(1.7)	(1.3)	(0.003)	
0.2–0.35	69.66	23.53	6.81	21.79	39.91	25.48	7.94	693.58	0.032	Sandy loam
	(5.3)	(6.1)	(3.5)	(4.3)	(3.0)	(2.4)	(1.5)	(1.5)	(0.010)	
0.35-0.50	67.58	21.82	10.61	23.37	41.35	25.10	9.91	592.70	0.034	Sandy loam
	(5.6)	(5.6)	(4.9)	(2.6)	(4.4)	(2.1)	(2.1)	(1.5)	(0.009)	

Note: *Sand = 2.0 – 0.05 mm, silt = 0.05 – 0.002 mm, and clay = < 0.002 mm (USDA classification); Standard deviations are reported in the parentheses (n=27 samples for each depth for the Particle size distribution and n= 9 samples for each depth for the initial SWC, θ_s, θ_{FC}, θ_{PWP}, EC and K_s). For K_s the values in the parentheses are geometric standard deviations.

2.4.3. Model recalibration

The AquaCrop model version 5.0 was used in this study. The calibrated maize crop parameters and other crop growth data of Gadédjisso-Tossou et al. (2018) were considered as a preliminary calibration of AquaCrop for maize in the present study. Thus, the observed values collected from the field experiment carried out on maize in Northern Togo from December 2017 to April 2018—detailed analysis of the data is presented in Gadédjisso-Tossou et al. (2019)—were used for the recalibration of AquaCrop. The field experiment consisted in assessing the impact of full irrigation (FI), 80% FI, and 60% FI management strategies on maize growth parameters and grain yield. In the present study, the evaluation of the performance of AquaCrop model for maize under FI, 80% FI, and 60% FI management strategies was done by comparing the field measurements of the above-ground biomass, CC, and grain yield at harvest to the simulated values.

The parameters used for the recalibration of AquaCrop for maize in Northern Togo include information about sowing, canopy cover and senescence, flowering, rooting depth, harvest index, soil management, and the maize cultivar. The options in AquaCrop to estimate the initial canopy cover from sowing rate, seed number, and the estimated germination rate was used to calibrate the CC. Then, the canopy expansion rates were automatically estimated by AquaCrop after we entered the phenological dates of emergence, maximum canopy cover, senescence, and maturity. The difference between the field data and the simulated values was lessened by using a trial and error approach until we reached the closest match. In general, the procedure was an iterative process of adjusting sensitive parameters, primarily crop-specific parameters in AquaCrop. The most sensitive crop parameters in AquaCrop model were reported in sensitivity analysis studies by Silvestro et al. (2017) and Jin et al. (2018). This process was accomplished for the above-ground biomass, CC, and grain yield at harvest under the FI, 80% FI, and 60% FI management strategies.

2.4.4. Model evaluation

In this study, the above-ground biomass, CC, and grain yield at harvest were considered for evaluating the goodness of fit between measured data and AquaCrop simulated results. Six statistical indicators were used: the coefficient of determination (R^2), the Root Mean Squared Error (RMSE), the normalised root mean square error (NRMSE), the Nash-Sutcliffe model efficiency coefficient (EF), Willmott's index of agreement (d-index), and Percentage bias (PBIAS).

The R^2 is defined as the squared value of the Pearson correlation coefficient. It indicates the strength of the relationship between variables (Greaves and Wang, 2016). R^2 can take values from 0 to 1, with values close to 1 indicating a good agreement between simulated and measured data (Raes et al., 2012). For crop simulation studies, $R^2 > 0.80$ is mostly recommended (Ma et al., 2011). R2 is written as follows:

$$R^2 = \left(\frac{\sum_{i=1}^{n}(O_i-\bar{O})(P_i-\bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i-\bar{O})^2}\sqrt{\sum_{i=1}^{n}(P_i-\bar{P})^2}} \right)^2 \quad (2)$$

Where:

O_i = measured data

$\bar{O}$ = average of the measured data

P_i = simulated data

$\bar{P}$ = average of simulated data

The RMSE, which is one of the most used statistical indicators (Jacovides and Kontoyiannis, 1995), measures the absolute model uncertainty (Heng et al., 2009). It varies from 0 to + ∞, with the former showing optimal and the latter poor model performance (Raes et al., 2012). Adeboye et al. (2019) reported that a value of 15% is considered "good" and 20% is "satisfactory" for agricultural models' evaluations. The RMSE is expressed in Eq. (3) as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i-O_i)^2}{n}} \quad (3)$$

Where:

n = number of measurements taken from the same treatment on different dates during the growing cycle.

The NRMSE is expressed as a percentage and empresses the relative difference between model and observations. It is expressed in Eq. (4) as:

$$NRMSE = \frac{1}{\bar{O}}\sqrt{\frac{\sum_{i=1}^{n}(P_i-O_i)^2}{n}} \times 100 \quad (4)$$

A simulation is considered excellent if NRMSE is less than 10%, good if between 10 and 20%, fair if between 20 and 30% and poor if greater than 30% (Jamieson et al., 1991).

The EF assesses the relative magnitude of the residual variance compared to the variance of the observations (Nash and Sutcliffe, 1970). EF ranges from – ∞ to 1, with the latter indicating a perfect match between simulated and observed data (Raes et al., 2012). Generally, performance is considered acceptable when the value is between 0 and 1. Values less than 0 signify that the mean of observed values is a better predictor than the simulated values and is poor performance (Moriasi et al., 2007). The Nash-Sutcliffe model efficiency coefficient is expressed (Eq. (5)):

$$EF = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \quad (5)$$

The index of agreement, d-index, measures the relative error in model estimates (Greaves and Wang, 2016). It varies from 0 to 1, with the former indicating poor and the latter a perfect agreement between the predicted and observed data (Krause et al., 2005). The index of agreement is calculated as follows (Willmott, 1982):

$$d - index = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \quad (6)$$

Gupta et al. (1999) reported that PBIAS assesses the average tendency of the simulated data to be greater or smaller than their measured data. It is determined as follows:

$$PBIAS = \frac{\sum_{i=1}^{n}(O_i - P_i)}{\sum_{i=1}^{n}(O_i)} \times 100 \quad (7)$$

Pereira et al. (2015) reported that 0 is the optimal value of PBIAS and low-magnitude values indicate accurate model simulation. They also added that positive values of PBIAS indicate model underestimation bias, while negative values show model overestimation bias. For evaluating crop simulation models, the PBIAS values of −15 to +15% represent the acceptable range (Ma et al., 2011).

2.5. Evaluation of the impact of soil and climate variability on the crop yield

In this study, we have investigated 48 synthetic soil scenarios and eight climate scenarios. These are soil synthetic scenarios generated with Rosetta 3 and Saxton and Rawls (2006) PTF based on sandy loam class and laboratory measurement data. The climate scenarios were based on the baseline, HadCM3, RCP4.5, and RCP8.5 climate of northern Togo. These are the scenarios SC 49 – SC 56 (Table 2). For all the soil scenarios assessed in this study, the wettest, average, and driest growing periods of the 100-year climate were considered. The summary can be seen in Table 2.

Table 2. Soil and climate scenarios investigated

<table>
<tr><td colspan="2" rowspan="3">Climate scenarios for soil variability</td><td colspan="4">Synthetic soil scenarios</td><td colspan="2" rowspan="2">Scenarios for climate variability</td></tr>
<tr><td colspan="2">Rosetta 3</td><td colspan="2">Saxton and Rawls (2006)</td></tr>
<tr><td>Sandy loam class (USDA)</td><td>Lab data</td><td>Sandy loam class (USDA)</td><td>Lab data</td><td>Rosetta lab (average soil)</td><td>Saxton lab (average soil)</td></tr>
<tr><td rowspan="3">Baseline climate</td><td>Wettest growing period</td><td>SC 1</td><td>SC 4</td><td>SC 7</td><td>SC 10</td><td rowspan="3">SC 49</td><td rowspan="3">SC 50</td></tr>
<tr><td>Average growing period</td><td>SC 2</td><td>SC 5</td><td>SC 8</td><td>SC 11</td></tr>
<tr><td>Driest growing period</td><td>SC 3</td><td>SC 6</td><td>SC 9</td><td>SC 12</td></tr>
<tr><td rowspan="3">HadCM3 climate</td><td>Wettest growing period</td><td>SC 13</td><td>SC 16</td><td>SC 19</td><td>SC 22</td><td rowspan="3">SC 51</td><td rowspan="3">SC 52</td></tr>
<tr><td>Average growing period</td><td>SC 14</td><td>SC 17</td><td>SC 20</td><td>SC 23</td></tr>
<tr><td>Driest growing period</td><td>SC 15</td><td>SC 18</td><td>SC 21</td><td>SC 24</td></tr>
<tr><td rowspan="3">RCP4.5 climate</td><td>Wettest growing period</td><td>SC 25</td><td>SC 28</td><td>SC 31</td><td>SC 34</td><td rowspan="3">SC 53</td><td rowspan="3">SC 54</td></tr>
<tr><td>Average growing period</td><td>SC 26</td><td>SC 29</td><td>SC 32</td><td>SC 35</td></tr>
<tr><td>Driest growing period</td><td>SC 27</td><td>SC 30</td><td>SC 33</td><td>SC 36</td></tr>
<tr><td rowspan="3">RCP8.5 climate</td><td>Wettest growing period</td><td>SC 37</td><td>SC 40</td><td>SC 43</td><td>SC 46</td><td rowspan="3">SC 55</td><td rowspan="3">SC 56</td></tr>
<tr><td>Average growing period</td><td>SC 38</td><td>SC 41</td><td>SC 44</td><td>SC 47</td></tr>
<tr><td>Driest growing period</td><td>SC 39</td><td>SC 42</td><td>SC 45</td><td>SC 48</td></tr>
</table>

SC = Scenario

Fig. 2 shows the synthetic cumulative rainfall of the field experiment growing period (December-April) for 100-years climate of northern Togo based on the baseline, HadCM3, RCP4.5, and RCP8.5 climate scenarios using LARS-WG. The cumulative rainfalls recorded during the wettest growing periods were 213 mm, 228 mm, 124 mm, and 135 mm for the baseline, HadCM3, RCP4.5, and RCP8.5 climate scenarios, respectively (Fig. 2). During the driest growing periods, for all the climate scenarios, no rainfall occurred. The distributions of the 100-year growing period data are skewed to the right with more than 50% of the growing periods standing between 0 mm and 25 mm cumulative rainfall (Fig. 3).

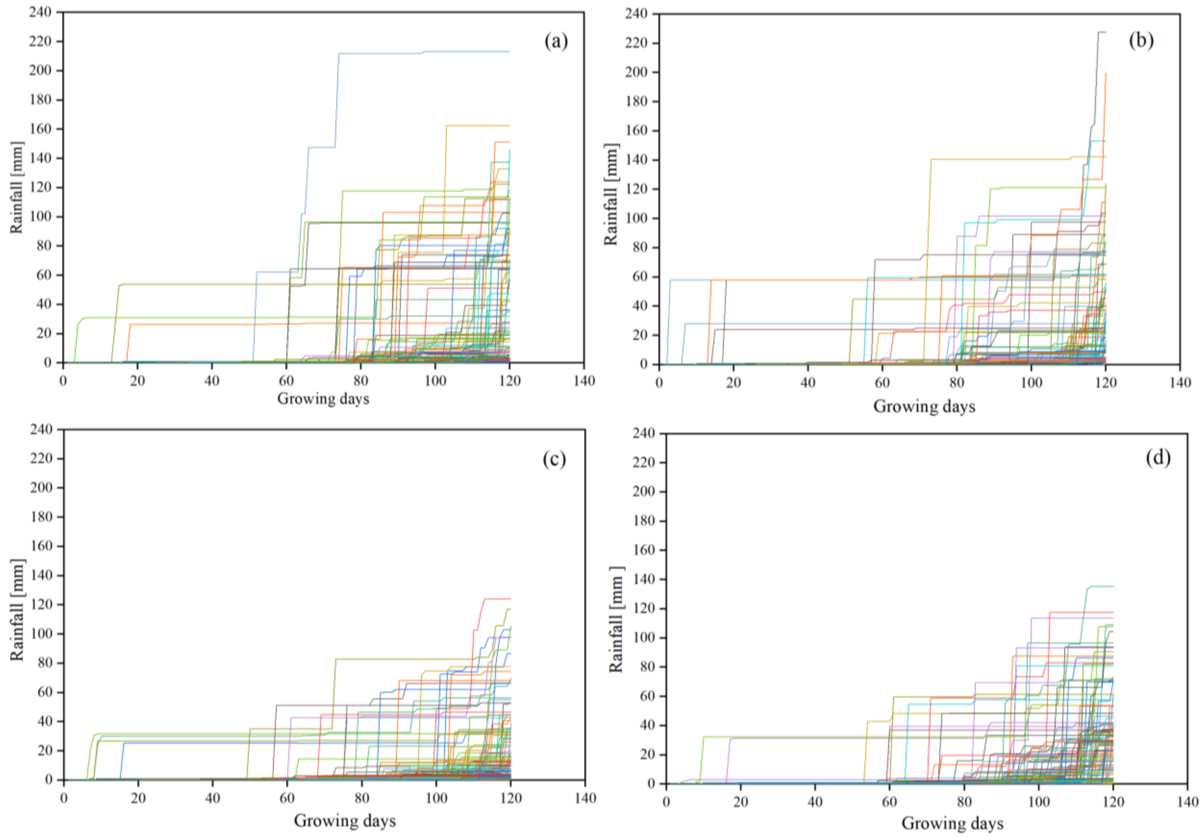

Fig. 2. Synthetic cumulative rainfall of the field experiment growing period (December-April) for a 100-year climate of northern Togo based on the climate scenarios: (a) baseline, (b) HadCM3, (c) RCP4.5, and (d) RCP8.5 using LARS-WG.

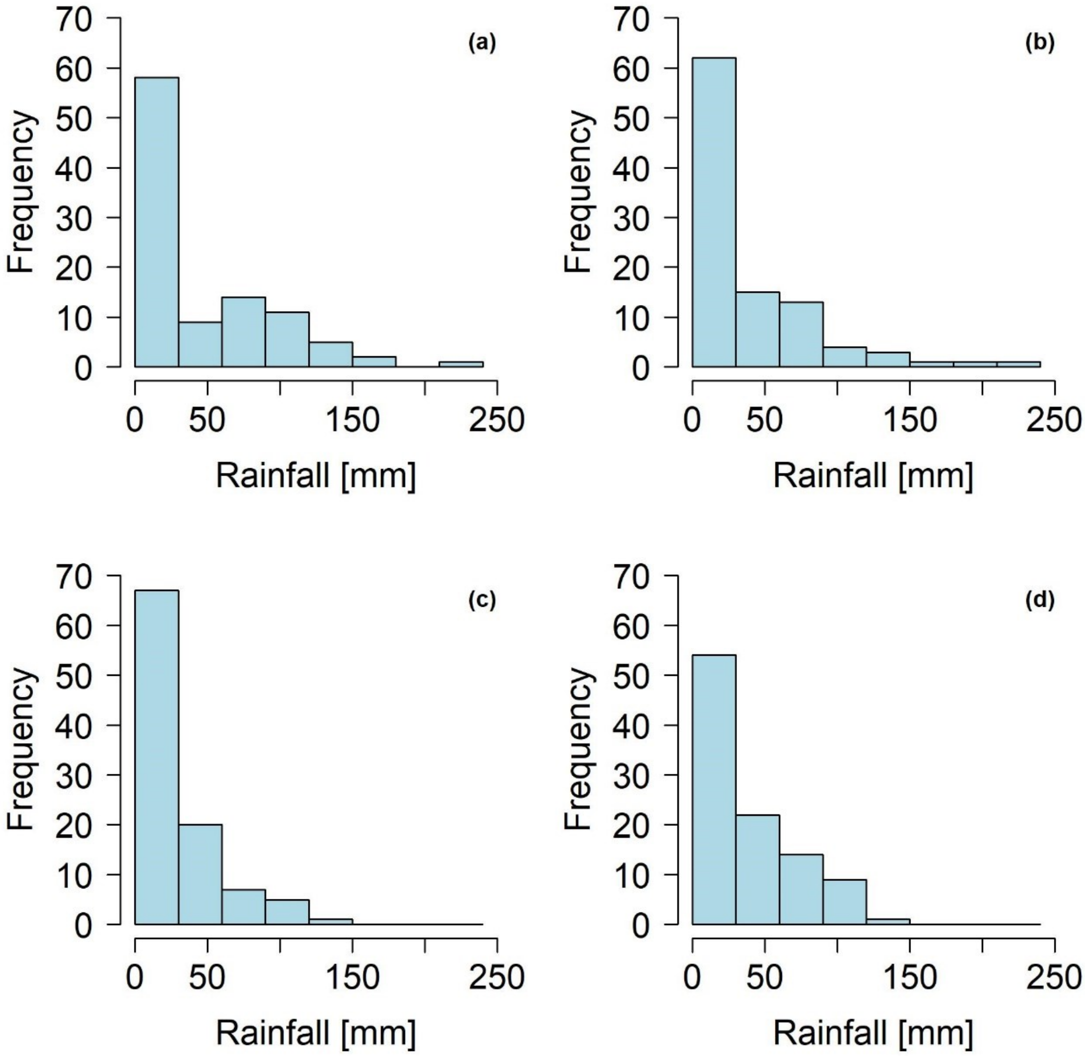

Fig. 3. Histogram of the distribution of the synthetic cumulative rainfall of the field experiment growing periods (December-April) for a 100-year climate of northern Togo based on the climate scenarios: (a) baseline, (b) HadCM3, (c) RCP4.5, and (d) RCP8.5 using LARS-WG.

Fig. 4 shows the framework used to simulate maize yield under the scenarios described above. It comprises: (i) the Long Ashton Research Station Weather Generator (LARS-WG) (Semenov et al., 1998), a weather generator, for simulating 100-year climate time series of baseline scenario for this study; (ii) the AquaCrop model (Hsiao et al., 2009; Raes et al., 2009; Steduto et al., 2009) which was utilised to simulate the crop yield during the growing season (Fig. 4, loop 1); and (iii) Global Evolutionary Technique for OPTimal Irrigation Scheduling (GET-OPTIS) (For more details see Schütze et al., 2012) which is a problem-specific programme for optimal irrigation scheduling under limited water supply (Fig. 4, loop 2). A volume of water is provided to GET-OPTIS, which produces an optimised irrigation schedule under a given climate, soil, and crop information. Then, this schedule is employed by AquaCrop model to simulate the crop yield. The statistical analysis of the outputs of the simulations using different exceedance probability level is call stochastic crop-water production functions (SCWPF) (Schütze and Schmitz, 2010). This framework was run through an open-source software developed to simulate and maximise crop-water productivity of deficit irrigation systems and named Deficit Irrigation Toolbox (DIT) (Schütze and Mialyk, 2019).

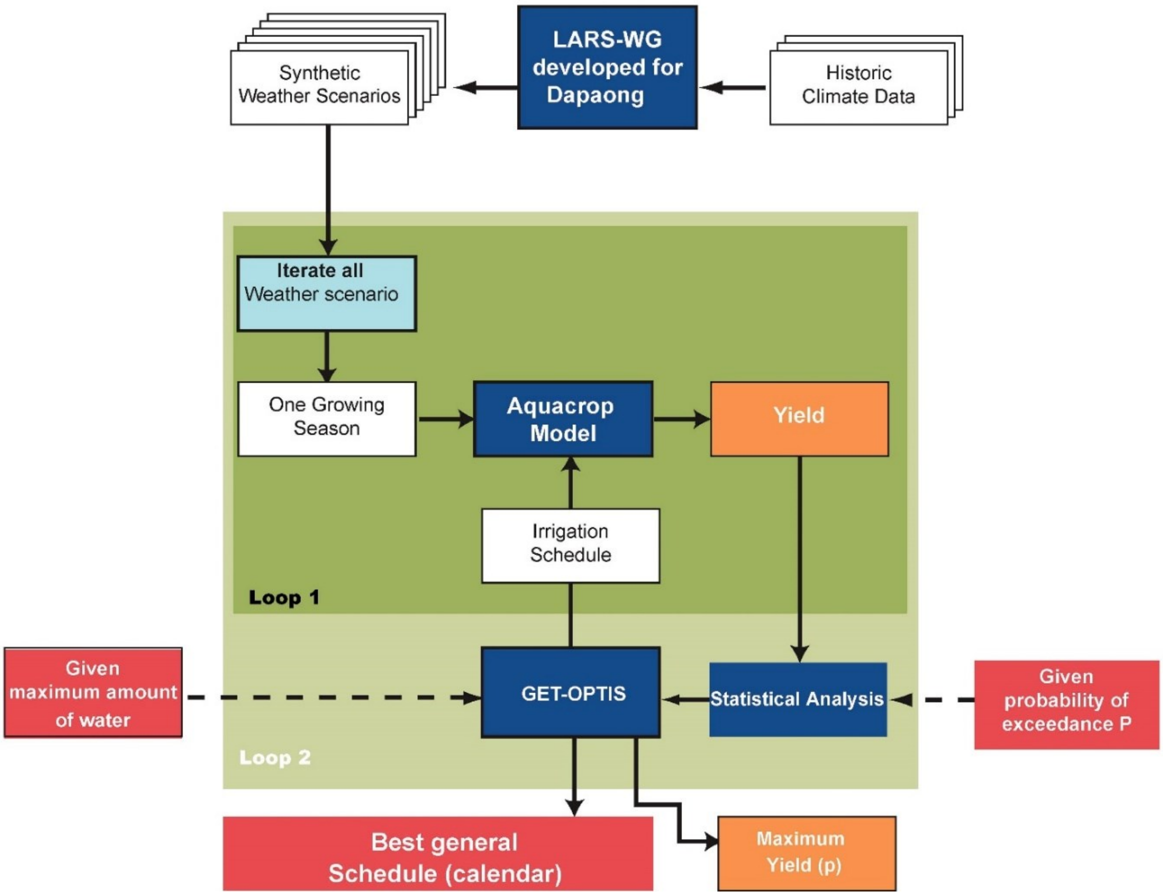

Fig. 4. General framework for generating stochastic crop water production functions (adapted from Schütze and Schmitz (2010) and. Gadédjisso-Tossou et al. (2018)).

3. Results and discussion

3.1. Examples of synthetic soil samples generated and predicted plant available water using PTFs

Fig. 5 shows examples of synthetic soil samples generated from the entire textural triangle, sandy loam class, and measured texture data according to USDA soil classification system. The soil texture generator can be used to generate random soil sample from the entire USDA soil texture triangle (Fig. 5a). In this study, to assess the soil variability impact on maize yield, the soil texture generator was utilised to sample from the sandy loam class of USDA soil classification system (Fig. 5b) and laboratory measurement data of soil texture of samples taken from the experimental site in northern Togo (Fig. 5c). The output of the sampling contains information about the texture. For the three examples depicted in Fig.5, the number of synthetic soil samples generated is 500.

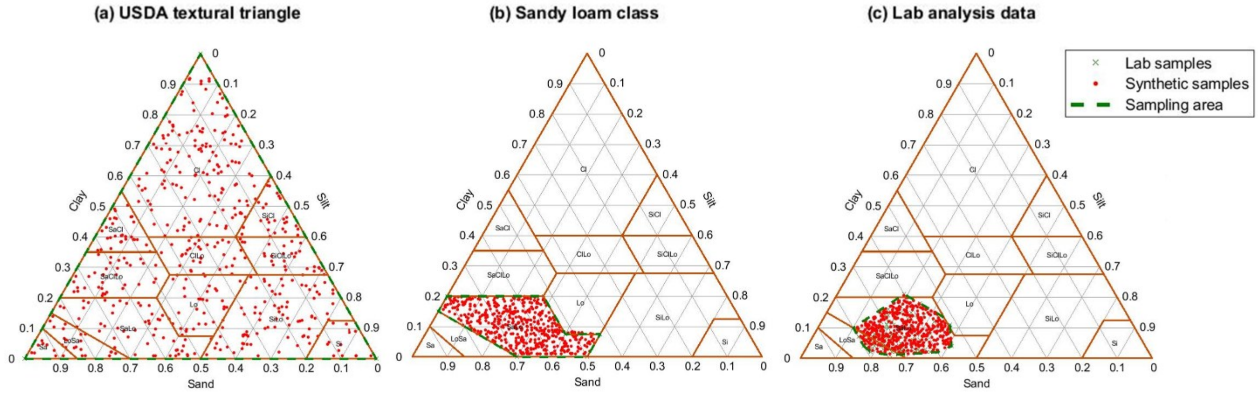

Fig. 5. Synthetic soil samples generated from the (a) entire textural triangle; (b) sandy loam class; and (c) texture analysis data according to USDA soil classification system (n = 500 random samples).

Fig. 6 shows the histograms of the distributions of the plant available water (PAW), which were used to assess the soil variability impact on maize yield in the study area. This soil property was predicted using the Rosetta 3 and Saxton and Rawls' (2006) pedotransfer functions. This was done considering the four soil depths presented in Table 1. It can be seen from Fig. 6a–d and i–l that the predicted values of PAW using Rosetta are in the same range as the laboratory measurements (the difference between θ_{FC} and θ_{PWP}) on average (Table 1). Thus, Rosetta 3 is adequate for estimating the hydraulic characteristics of the soil in northern Togo. However, it has slightly overestimated the values of PAW for northern Togo. These findings are supported by the results presented by Rubio and Llorens (2004) and Gérard et al. (2004), who used the first version of Rosetta. Nevertheless, Saxton and Rawls (2006) underestimated the predicted values of PAW for northern Togo when compared to the laboratory analysis (Fig. 6e–h and m–p). This indicates that Saxton and Rawls (2006) seems to not perform well for these parameters (Han et al., 2015). The random soil samples generated from sandy loam class (Fig. 6a, c, e, g, i, k, m, and o) show higher standard deviations than that of laboratory texture analysis data (Fig. 6b, d, f, h, j, l, n, and p) regardless of the soil depth considered. This means that high accuracy in the data leads to low variability in the distribution.

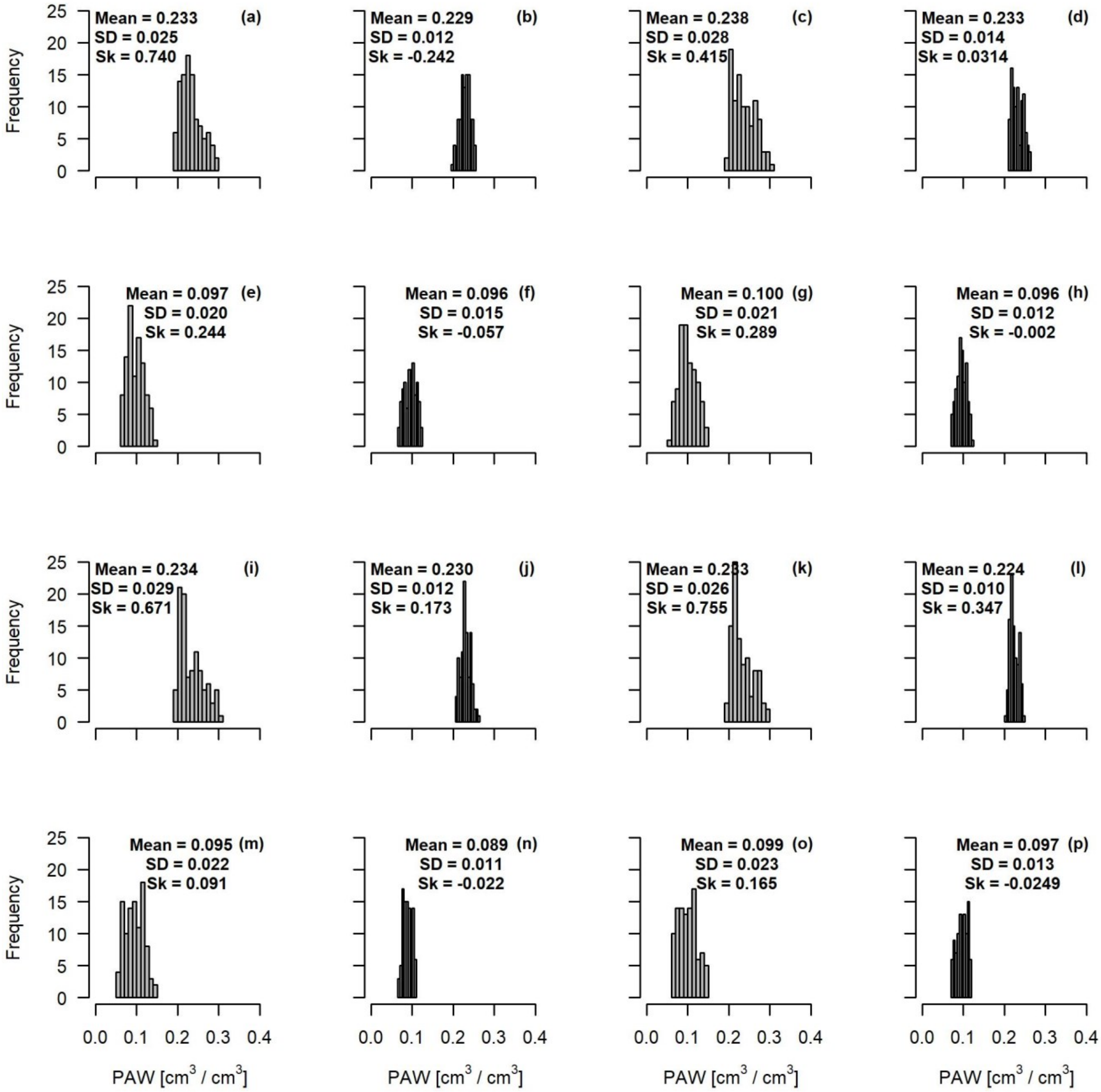

Fig. 6. Plant Available Water (PAW) for synthetic soil generated (n = 100) from sandy loam class (USDA) using Rosetta3 ((a) soil layer 1, (c) soil layer 2, (i) soil layer 3, (k) soil layer 4); from lab data using Rosetta3((b) soil layer 1, (d) soil layer 2, (j) soil layer 3, (l) soil layer 4); from sandy loam class (USDA) using Saxton and Rawls ((e) soil layer 1, (g) soil layer 2, (m) soil layer 3, (o) soil layer 4); and from lab data using Saxton and Rawls ((f) soil layer 1, (h) soil layer 2, (n) soil layer 3, (p) soil layer 4). The values on the graphs represent the mean, standard deviation (SD) and skewness (sk). Soil layer 1 = 0–0.1 m, layer 2 = 0.1–0.2 m, layer 3 = 0.2–0.35 m, and layer 4 = 0.35–0.5 m.

3.2.Recalibration

Table 3 shows the main parameters used to calibrate the AquaCrop model for simulating maize growth and productivity for the study location. The harvest index (HI) used in the AquaCrop model (26%) (Gadédjisso-Tossou et al., 2019) was lower than the proposed 48% (Heng et al., 2009; Hsiao et al., 2009) because of the low yielding maize variety (TZEE-W) used in this study. Similar values of HI were used by Abedinpour et al. (2012), who evaluated the performance of AquaCrop for maize in a semi-arid environment. Also, in our study, the AquaCrop model was run in growing degree days (GDD) mode.

Table 3. Non-conservative parameters adjusted to recalibrate the model for simulating the response of maize to different irrigation management strategies in northern Togo.

Parameter Description	Value	Units or Meaning
Time from sowing to emergence	8 (135)	DAP(GDD)
Time to maximum canopy cover	69(1,199)	DAP(GDD)
Time from sowing to maximum rooting depth	86 (1,257)	DAP(GDD)
Time from sowing to start of canopy senescence	90 (1,408)	DAP(GDD)
Time from sowing to maturity	111 (1,898)	DAP(GDD)
Time from sowing to flowering	66 (1,018)	DAP(GDD)
Duration of flowering	18 (183)	DAP(GDD)
Length of building up HI	39(778)	DAP(GDD)
Maximum effective rooting depth, Z	0.5	meter
Minimum effective rooting depth, Zn	0.3	meter
Reference harvest index, HI	26	%
Cultivar (TZEE-W)	–	TZEE-W
Planting method	–	Direct sowing
Sowing date	16-Dec	Date
Planting density	70,000	Plants/ha
Surface mulches	0	%
Curve number, CN	46	–

DAP = days after planting; GDD = growing degree days; HI = harvest index.

Table 4 presents the maize crop's response to soil fertility stress based on the field data. The relative dry above-ground biomass production (60%), maximum canopy cover (78%), and canopy decline in the growing season (medium) under soil fertility stress were provided to the model based on observed data. Then, the model ran an automatic calibration for the soil fertility stress. In this region, 200 kg ha^{-1} composite fertiliser (N15P15K15) together with 100 kg ha^{-1} urea (46% N) is the reference for soil fertility for maize cropping (Laba and Sogbedji, 2015 and Mathe et al., 2008). The calibrated crop response to soil fertility stress for FI treatment was used to simulate the maize yield for the soil and climate impact assessment in the current study.

Table 4. The relative dry above-ground biomass production (Brel), maximum canopy cover (CCx), and canopy decline in the growing season together with the resulting calibrated effect of soil fertility stress on canopy growth coefficient (CGC), CCX, canopy decline, and biomass water productivity (WP*) used in simulating maize growth in Dapaong (northern Togo).

Crop: Maize	
Calibration location	Dapaong (northern Togo)
Input for calibration	
Brel (%)	60
CCx under soil fertility stress (%)	78
Canopy decline	Medium
Results of calibration	
CGC reduction (%)	15
CCx reduction (%)	1
Average canopy cover decline (%/ day)	0.42
WP* decline (%)	70

3.2.1 Canopy Cover

Fig. 7a–c shows the development in the green CC for the entire growing season. In general, simulated CC agreed well with the measured CC. The accuracy of the calibrated AquaCrop model in predicting CC development was confirmed by the statistical indicators presented in Table 5. However, the AquaCrop tended to underestimate CC during the mid-season growth stage (Fig. 7a–c). This was substantiated by the positive PBIAS obtained for all treatments (Table 5). Low RMSE and high EF for all treatments showed that the model is robust in simulating CC development for different irrigation strategies in northern Togo. Specifically, high EF values obtained (> 0.93) suggested that the residual variance was much smaller than the measured data variance (Paredes et al., 2014).

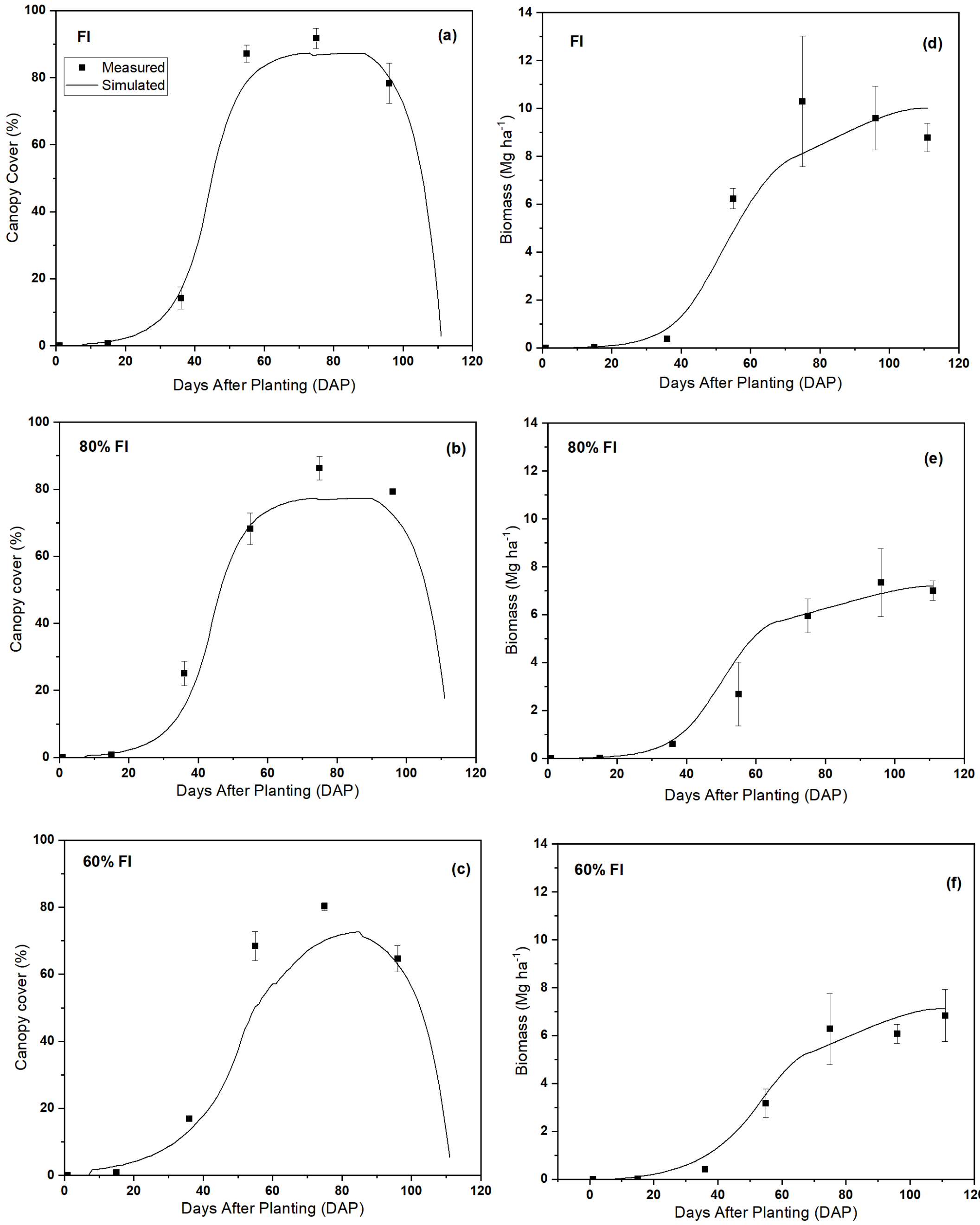

Fig. 7. Measured and simulated canopy cover under (a) full irrigation (FI), (b) 80% FI, and (c) 60% FI; and above-ground biomass under (d) FI, (e) 80% FI, and (f) 60% FI for maize using the calibrated parameters in northern Togo. Vertical bars indicate standard deviations (n = 9).

There was a strong correlation between the measured and simulated CC for all treatments (R^2 > 0.99). Our results are endorsed by those reported by Greaves and Wang (2016) and Yemane et al. (2015). The RMSE values obtained ranged from 4.2 to 8.6% for all treatments. These RMSE values for FI and 80% FI treatments are in the range or smaller than those reported by Paredes et al. (2014), with RMSE ranging from 4.6 to 7.4%. Hsiao et al. (2009) reported greater RMSE ranging from 4.8 to 13.6%. Higher values of RMSE were reported by Heng et al. (2009) for rainfed maize, with RMSE ranging from 7.2 to 34.5%. Also, 13.1% of RMSE was reported by García-Vila and Fereres (2012). The NRMSE comparison between the simulated and measured CC showed a difference of 9.2% for FI treatment, which indicates a perfect result. However, the water stress experienced by the 60% FI resulted in the NRMSE of 22.4% (Table 5), showing that as water stress increases model accuracy lessens. This result is supported by the findings of Greaves and Wang (2016).

Table 5. Statistical indicators of the performance of AquaCrop in simulating canopy cover and above-ground biomass for maize under different irrigation management strategies in northern Togo.

	Treatment		
Statistical indicators	FI	80% FI	60% FI
Variable		Canopy cover	
R^2	0.99	0.99	0.99
RMSE (%)	4.20	6.20	8.60
NRMSE	9.20	14.30	22.40
EF	0.99	0.97	0.93
d–index	0.99	0.99	0.98
PBIAS	3.23	10.33	15.67
Variable		Above-ground biomass	
R^2	0.97	0.98	0.99
RMSE (Mg ha^{-1})	1.10	0.60	0.50
NRMSE	21.50	18.90	13.90
EF	0.94	0.96	0.98
d–index	0.98	0.99	0.99
PBIAS	5.69	–6.46	–5.66

FI = Full Irrigation.

3.2.2 Above-ground biomass and grain yield

Fig. 7d–f shows the development in the above-ground biomass of maize for the entire growing season for all treatment. In general, the model simulated the above-ground biomass production throughout the growing season well for all the treatments (Fig. 7d–f), as indicated by the low RMSE and high d–index and EF in Table 5. The simulated values correlated strongly with the measured values (R^2 > 0.97). These results are corroborated by those of Akumaga et al. (2017) who assessed the performance of AquaCrop model in simulating rainfed maize growth in Nigeria. For instance, the simulated above-ground biomass showed a good fit with the measured one with R^2 of 0.98 (d–index= 0.99, EF = 0.96) for the 80% FI (Table 5). A smaller value of EF was reported by Paredes et al. (2014) (0.81). However, the model tended to overestimate the above-ground biomass during the mid- and late season growth stages especially for 80% and 60% FI treatments with PBIAS of –6.46 and –5.66, respectively (Table 5). Greaves and Wang (2016) reported similar findings. The RMSE obtained are small, with values ranging from 0.5 to 1.1 Mg ha^{-1}. Abedinpour et al. (2012) and Akumaga et al. (2017) reported similar values of RMSE. Nevertheless, the RMSE values reported by Paredes et al. (2014) and Heng et al. (2009) (for deficit irrigation condition) are larger.

Table 6 presents the values of the simulated final above-ground biomass and grain yield at harvest and their deviation from the measured data. The final above-ground biomass measured in the field ranged from 6.8 to 8.8 Mg ha^{-1}, while simulated values ranged from 7.1 to 9.9 Mg ha^{-1} (Table 6). The deviation is positive for all treatments. This means that the model overestimated the final above-ground biomass for all treatments. Similar results were obtained by Yemane et al. (2015) and Abedinpour et al. (2012). It should be noted that the yield deviations for FI and 80% are smaller than the one of 60% FI treatment. This means that less water stress implies better model performance. Using different maize cultivars and model parameter values, Heng et al. (2009) reported much lower deviations from measured values of yield. The measured grain yield at harvest varied between 1.1 and 2.2 Mg ha^{-1} among treatments, while simulated values ranged from 1.6 to 2.6 Mg ha^{-1} (Table 6). The positive deviations showed that the model overestimated the grain yield for all treatments. However, statistical indicators such as R2, RMSE, NRMSE, EF, d–index, and PBIAS for CC and above-ground biomass suggested that the model can be used to simulate maize grain yield in northern Togo accurately. These results are corroborated by those reported by Stricevic et al. (2011) who assessed the performance of AquaCrop in simulating maize yield under rainfed and supplemental irrigation conditions in a drought-prone area of Serbia.

Table 6. Simulated compared with measured values of above-ground biomass and grain yield at harvest under different irrigation management strategies in northern Togo.

Treatment	Final above-ground biomass			Grain yield		
	Measured (Mg ha^{-1})	Simulated (Mg ha^{-1})	Deviation (%)	Measured (Mg ha^{-1})	Simulated (Mg ha^{-1})	Deviation (%)
FI	8.8 (1.3)*	9.9	12.5	2.2 (0.1)	2.6	18.2
80% FI	7.0 (1.5)	7.3	2.9	1.8 (0.4)	1.9	5.6
60% FI	6.8 (1.0)	7.1	4.4	1.1 (0.5)	1.6	45.5

*Values in the parentheses represent standard deviations (n = 3 for grain yield and 9 for biomass); FI = Full Irrigation.

3.3. Impact of soil and climate variability on maize yield

Fig. 8 shows the soil sample stability analysis for irrigation storage of 200 mm to 500 mm using the baseline climate data. It may be concluded that 100 soil samples represent the number from which the maize yield becomes stable at all irrigation storage regardless of the exceedance probability considered (Fig. 8). Thus, 100 random soil samples were generated for the soil variability impact analysis on maize yield in the study area (Fig. 6).

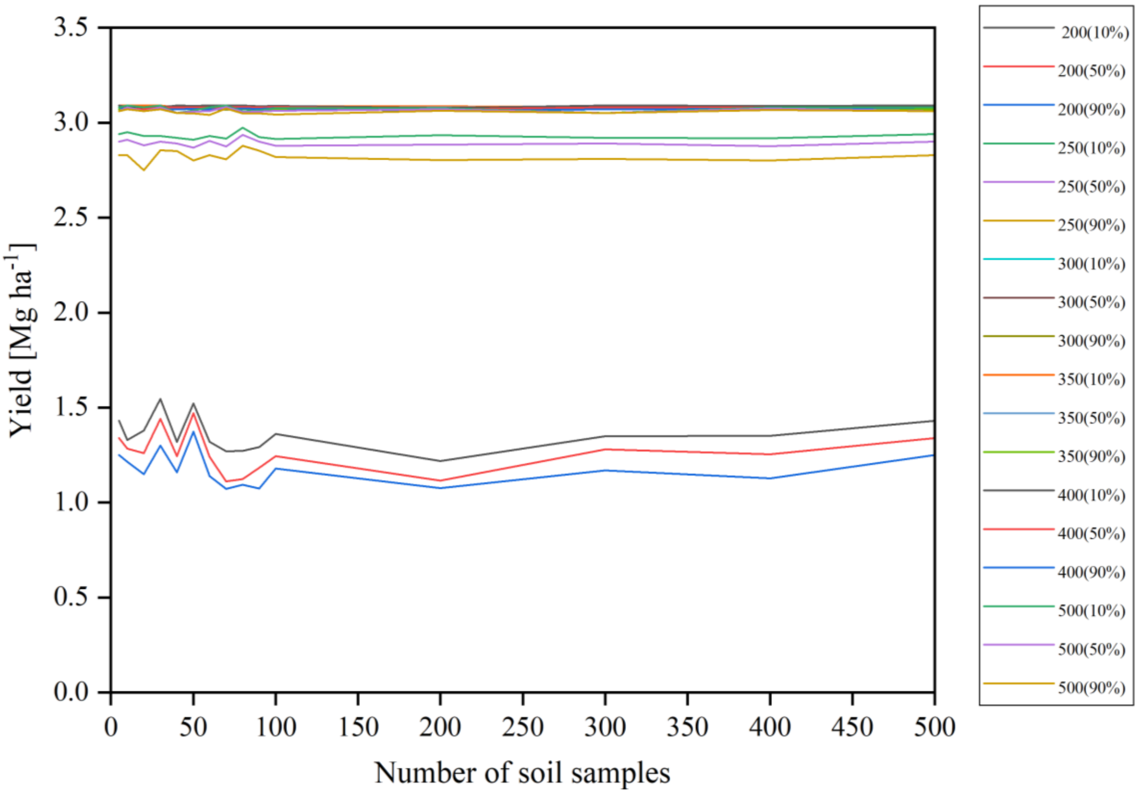

Fig. 8. Soil sample stability analysis for 200 mm to 500 mm of irrigation storage. The values in parentheses represent exceedance probability.

3.3.1. Effects of soil variability on maize yield

Fig. 9 and 10 show the crop water production functions of the expected maize yields, which can be achieved under the synthetic soil predicted with Rosetta 3. The soil scenarios under the baseline climate (SC 1–6) show a maximum expected yield of 2.9 Mg ha^{-1} on average, which was achieved with a minimum of 350 mm of irrigation storage (Fig. 9a–f). While, for the soil scenarios under the HadCM3 climate (SC 13-18), at least 450 mm of irrigation storage was needed reach the maximum expected yield of 2.5 Mg ha^{-1} on average (Fig. 9g–l). This means that the full irrigation is reached between 350 mm and 450 mm of net requirement irrigation storage under the soil scenarios mentioned above. It can also be noted that the crop water production functions for the three exceedance probabilities considered in this study (10%, 50%, and 90%) have nearly coincided (Fig. 9). This means that there is low variability in the expected maize yields obtained, which may originate from the distribution of the synthetic soil data used.

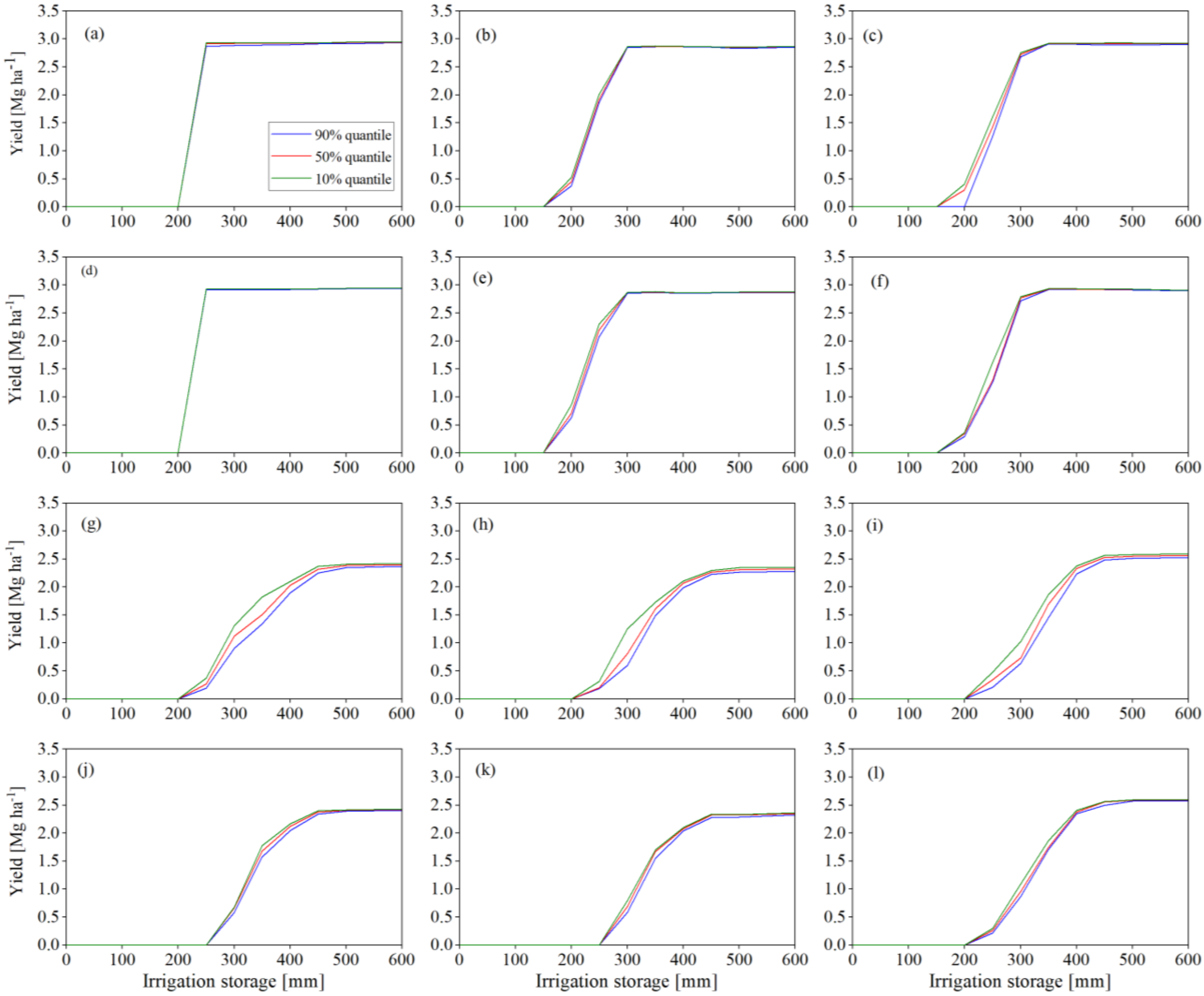

Fig. 9. Stochastic crop-water production function for: (a) scenario 1, (b) scenario 2, (c) scenario 3, (d) scenario 4, (e) scenario 5, (f) scenario 6, (g) scenario 13, (h) scenario 14, (i) scenario 15, (j) scenario 16, (k) scenario 17, and (l) scenario 18.

The soil scenarios under RCP4.5 (SC 25–30) and RCP8.5 (SC 37–42) climate show maximum expected yields of 2.7 Mg ha^{-1} and 2.8–3 Mg ha^{-1} on average, respectively, which were obtained with a minimum of 350 mm of irrigation storage (Fig. 10). Also, the crop water production functions for the three exceedance probabilities are almost matching, denoting a low variability in the expected maize yields achieved. Recently, Gadédjisso-Tossou et al. (2019) reported similar results (2.2 Mg ha^{-1}) in an experimental study conducted in the same area. The difference between the simulated yields and the measured ones can be explained by the fact that the maize plants might have been subjected to heat stress and diseases. Also, the optimally controlled deficit irrigation (< 350 mm) seems to save water and improve the yield (Abdalhi and Jia, 2018; Bell et al., 2018; Greaves and Wang, 2016; Hergert et al., 2016). The improvement observed in the maize yields is likely due to the optimisation of the irrigation schedules by GET-OPTIS. It can be concluded that the AquaCrop model is a valuable tool for predicting maize crop yield under different soil and climate conditions if it is well calibrated (Heng et al., 2009; Stricevic et al., 2011).

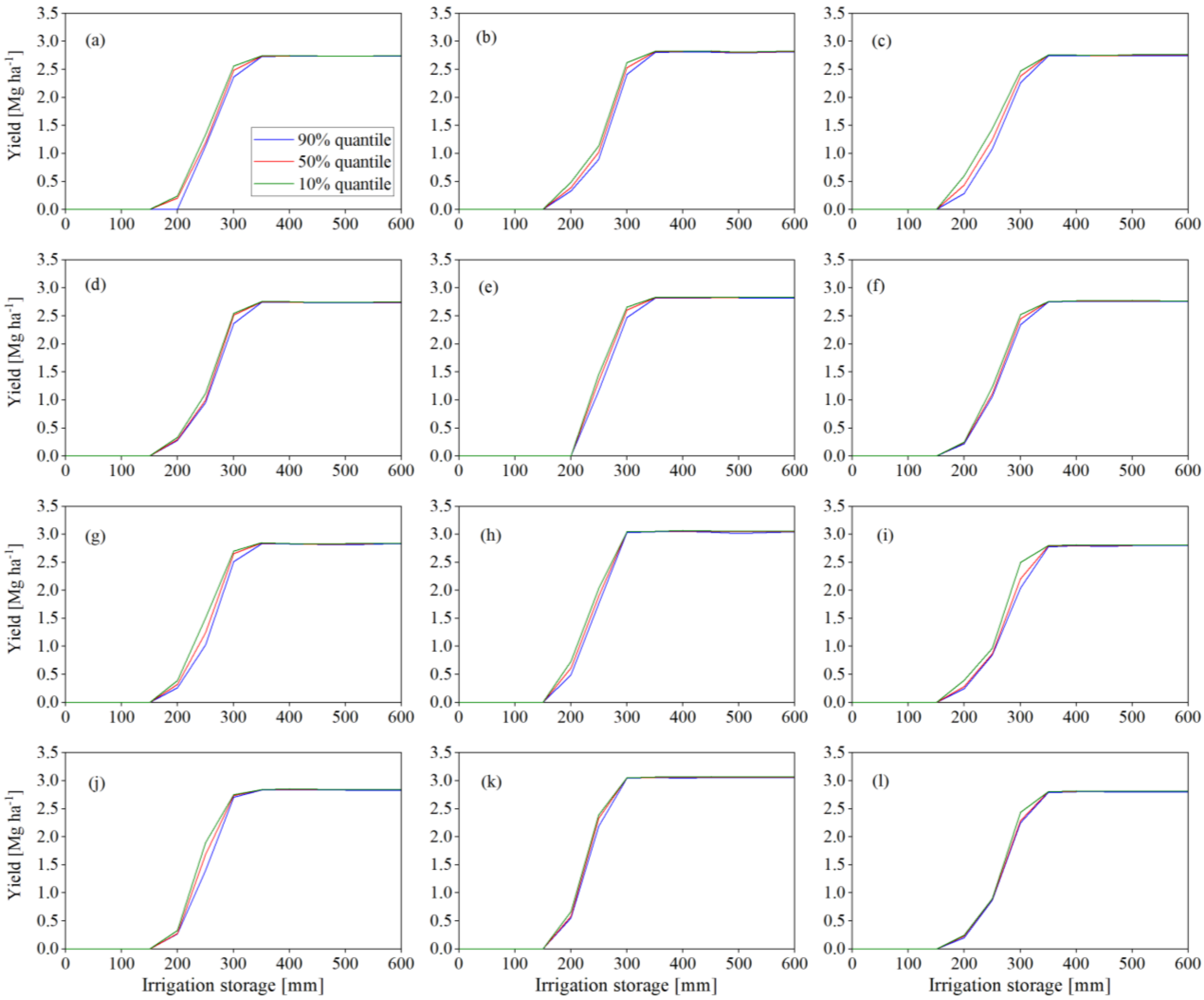

Fig. 10. Stochastic crop-water production function for: (a) scenario 25, (b) scenario 26, (c) scenario 27, (d) scenario 28, (e) scenario 29, (f) scenario 30, (g) scenario 37, (h) scenario 38, (i) scenario 39, (j) scenario 40, (k) scenario 41, and (l) scenario 42.

Fig. 11 and 12 show the crop water production functions of the expected maize yields, which can be achieved under the synthetic soil predicted with Saxton and Rawl (2006). The soil scenarios under the baseline climate (SC 7–12) show a maximum expected yield of 2.9

Mg ha^{-1} on average, which was achieved with a minimum of 350 mm of irrigation storage (Fig. 11a–f). While, for the soil scenarios under the HadCM3 climate (SC 19-24), at least 500 mm of irrigation storage was needed reach the maximum expected yield of 2.4 Mg ha^{-1} on average (Fig. 11g–l). Here also, there is low variability in the expected maize yields obtained, which may originate from the distribution of the synthetic soil data used.

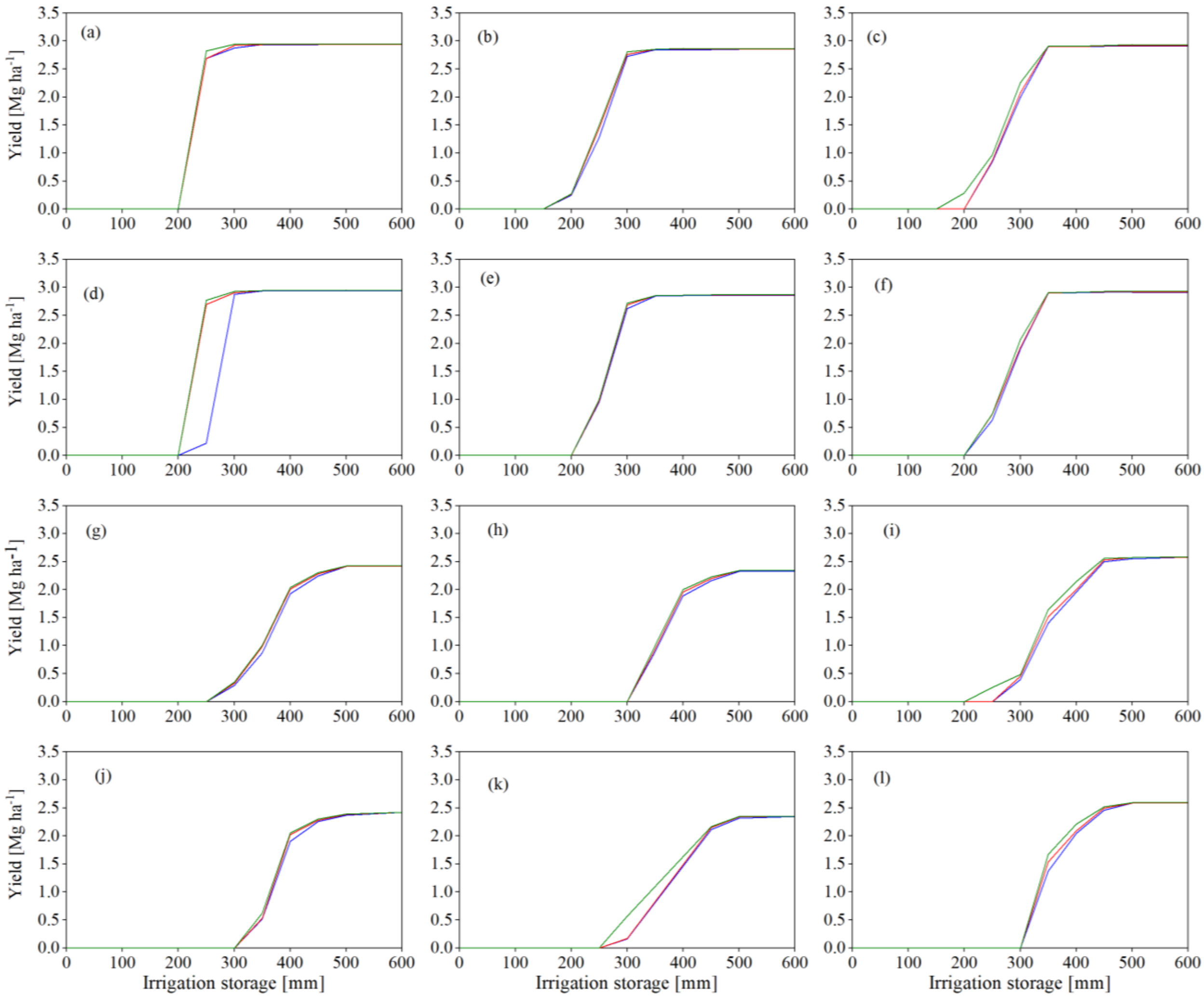

Fig. 11. Stochastic crop-water production function for: (a) scenario 7, (b) scenario 8, (c) scenario 9, (d) scenario 10, (e) scenario 11, (f) scenario 12, (g) scenario 19, (h) scenario 20, (i) scenario 21, (j) scenario 22, (k) scenario 23, and (l) scenario 24.

Also, The soil scenarios under RCP4.5 (SC 31–35) and RCP8.5 (SC 43–48) climate show maximum expected yields of 2.8 Mg ha^{-1} on average, which were achieved with at least 350 mm of irrigation storage (Fig. 12). Also, the crop water production functions for the three exceedance probabilities are almost overlapping, indicating a low variability in the expected maize yields achieved. Similarly, Diarisso et al. (2016) reported that soil variability influences crop yields in the savannah zones of Burkina Faso, of West Africa.

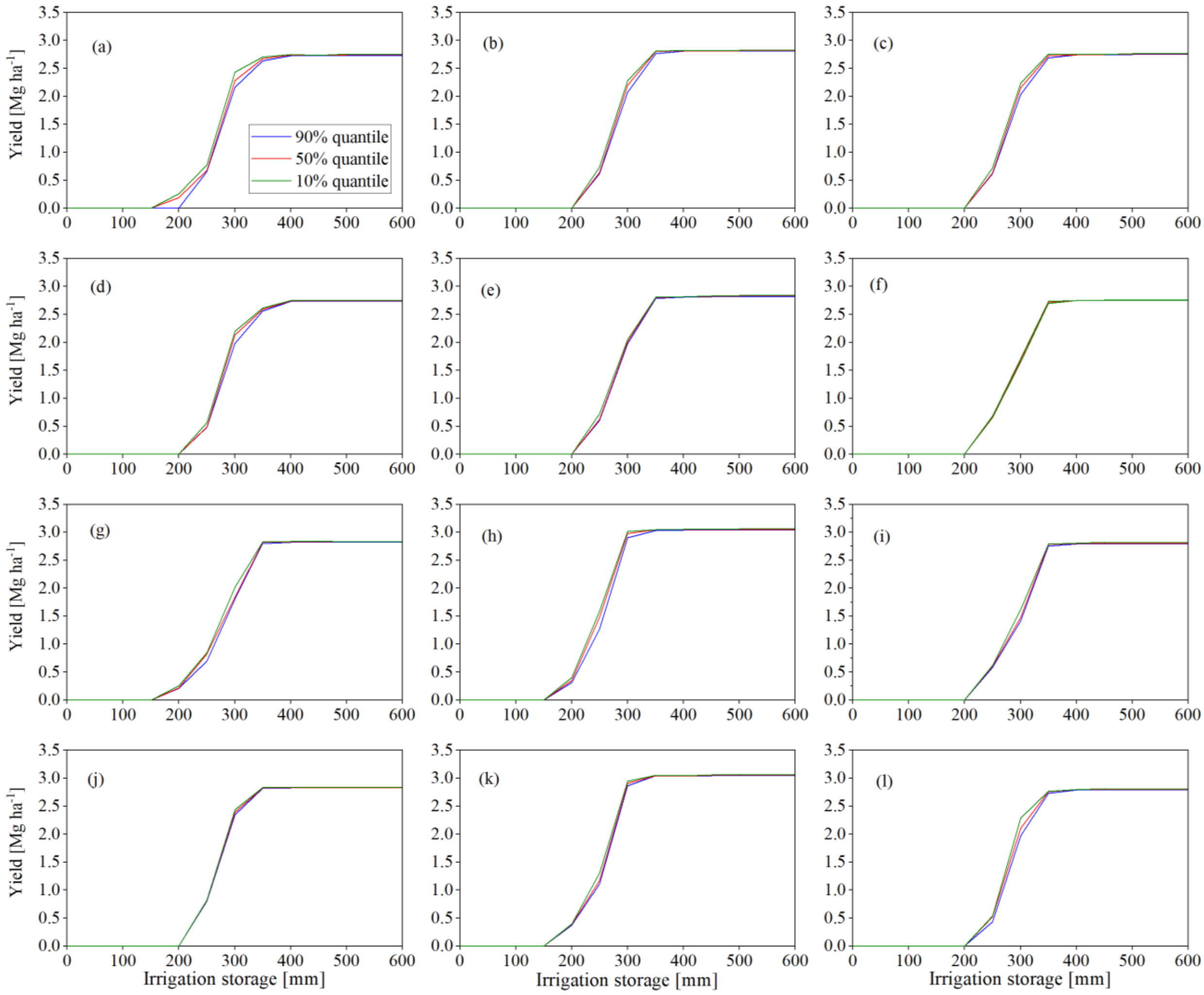

Fig. 12. Stochastic crop-water production function for: (a) scenario 31, (b) scenario 32, (c) scenario 33, (d) scenario 34, (e) scenario 35, (f) scenario 36, (g) scenario 43, (h) scenario 44, (i) scenario 45, (j) scenario 46, (k) scenario 47, and (l) scenario 48.

3.3.2. Effects of climate variability on maize yield

The stochastic crop-water production functions for optimised irrigated maize crop in the dry season in northern Togo under baseline, HadCM3, RCP4.5, and RCP8.5 are shown in Fig. 13. For all the eight climate variability scenarios (SC 49–56), at 10% exceedance probability the maximum maize yield achieved was 2.8 Mg ha^{-1} on average, will with 90% exceedance probability 2.5 Mg ha^{-1} was obtained on average (Fig. 13). The difference between the simulated yields of the 10% and 90% exceedance probability denotes the variability in the simulated yields, which may originate from the variability in the climate datasets used for the simulation. It can be concluded that climate variability may lead to high variability in the maize yields of northern Togo than soil variability does. The full irrigation storage was attained between 400 mm and 500 mm under the climate variability scenarios (Fig. 13). The climate variability scenarios run with soil samples simulated with Rosetta 3 (Fig. 13a, c, e, and g) show that 200 mm irrigation is needed to start having maize yield, while for the climate variability scenarios run with soil samples from Saxton and Rawl (2006) (Fig. 13b, d, f, and h), a higher irrigation storage is required (200–300 mm). This can be explained by the fact that the synthetic soil samples obtained from Rosetta 3 have higher PAW than that of Saxton and Rawl (2006) (Fig. 6).

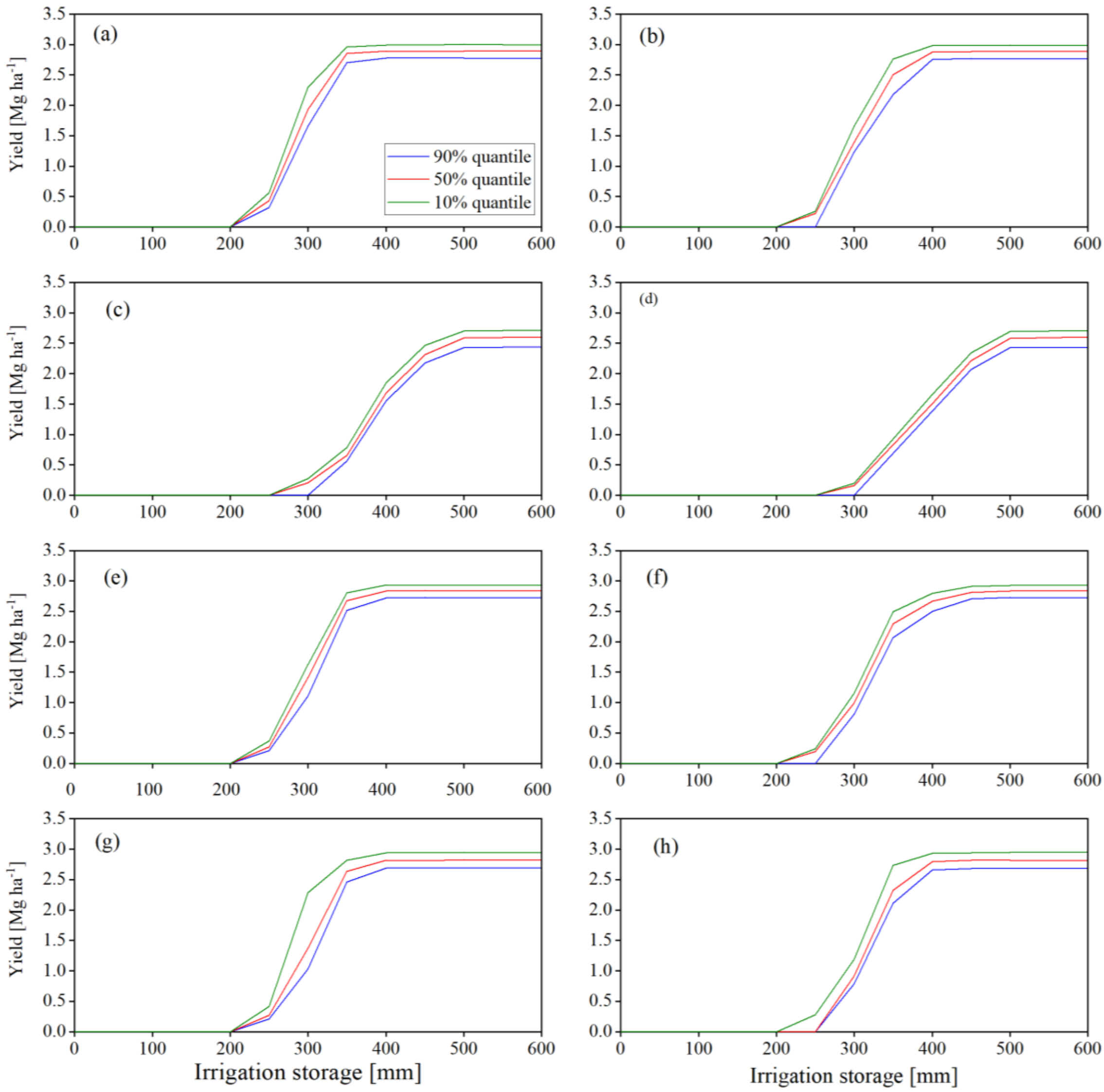

Fig. 13. Stochastic crop-water production function for: (a) scenario 49, (b) scenario 50, (c) scenario 51, (d) scenario 52, (e) scenario 53, (f) scenario 54, (g) scenario 55, and (h) scenario 56.

3.4. Summary of the Discussion

The conversion of the basic soil property data of northern Togo into soil hydraulic characteristics showed that Rosetta 3 overestimated the PAW slightly, while Saxton and Rawls (2006) underestimated it. Also, the distribution of the PAW from Rosetta 3 present higher variability than that of Saxton and Rawls (2006). The calibration of the AquaCrop model showed a good match between the measured and estimated canopy cover, above-ground biomass and grain yield data, indicating that the simulated maize yields obtained in this study were accurate. Under all the soil variability scenarios, the crop water production functions for the three exceedance probabilities considered in this study (10%, 50%, and 90%) have nearly coincided, while for all the climate variability scenarios there is a difference or a wide envelope between the crop water production functions of 10% and 90% exceedance probability. This suggests that climate variability may lead to high variability in the maize yields of northern Togo than soil variability does.

There are a few warnings that readers should consider when interpreting the findings of this study. Crop model simulations are subject to several uncertainties. AquaCrop supposes a disease- and pest-free environment and examines no effect of weed or extreme climate events such as flooding. Another point worth considering is that synthetic soil samples used in this study represent another source of uncertainty since they are outputs of a computer program. Finally, one should keep in mind that since the PTF used in this study were not initially developed for our study area, the accuracy of the hydraulic data obtained from them is questionable; however, the simulated values matched well with laboratory analysis data of soil samples from the study area.

4. Conclusions

The Impact of climate and soil variability on maize (*Zea mays L.*) yield was assessed considering several scenarios of soil and climate variability in the savannah region of northern Togo, West Africa. For this, AquaCrop was used as the crop growth simulation model. A field experiment was conducted on maize from December 2017 to April 2018 to validate the AquaCrop preliminary calibration for the study area. A soil texture generator was developed and applied to assess the impact of soil variability on the expected maize yield. Rosetta 3 and Saxton and Rawls (2006) pedotransfer functions were utilised to convert the synthetic basic soil data into hydraulic characteristics which served as inputs for the crop model.

The AquaCrop model requires relatively few input variables. Nonetheless, from the results of the calibration, it can be inferred that the AquaCrop model could be used to simulate the maize yield with acceptable accuracy under different irrigation management strategies in data-scarce regions like West Africa. We found that the maximum expected maize yield ranged from 2.5 to 3 Mg ha^{-1} considering all the scenarios investigated in this study. Also, the full irrigation storage was reached between 350 mm and 500 mm when all scenarios assessed are considered. The expected maize yields have been improved under the optimal controlled deficit irrigation using GET-OPTIS for all scenarios. It can be concluded that climate variability may lead to high variability in the maize yields of northern Togo than soil variability does.

This study gives substantial insights about maize crop response to the deficit and full irrigation strategies in northern Togo. It may be reproduced at other sites in the West African region in order to establish a regional water management strategy for food security enhancement. Establishing such a strategy will require to consider farmers' social, demographic, and economic conditions for a comprehensive assessment. Moreover, putting in place such a strategy will necessitate enhancing water supply in the area. This includes large- and small-scale water harvesting, access to groundwater, and wastewater use. Also, the right water governance and institution capacity will be needed to guarantee a sustainable use and an equitable distribution of water and its benefits among farmers.

Acknowledgements

This study was supported by a grant to A.G.-T. PhD scholarship under the Merit Scholarship Programme (MSP) 2015/2016 of the Islamic Development Bank (IsDB). Also, the United Nations University Institute for Integrated Management of Material Fluxes and Resources (UNU-FLORES) and Technische Universität Dresden (TUD) partially funded this study. We gratefully acknowledge the logistical assistance received from the UNU-FLORES and TUD. We appreciate the administration of the national meteorological service of Togo for providing us with the climate data. We thank the Togolese National Agricultural Institute for providing advisory services on the cultivar of maize used for the study. We would like to thank the agricultural technicians who rendered technical assistance during the fieldwork. We thank anonymous reviewers for their constructive criticisms.

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B. Histograms of distributions of the expected maize yield in northern Togo (scenarios in the third paper)

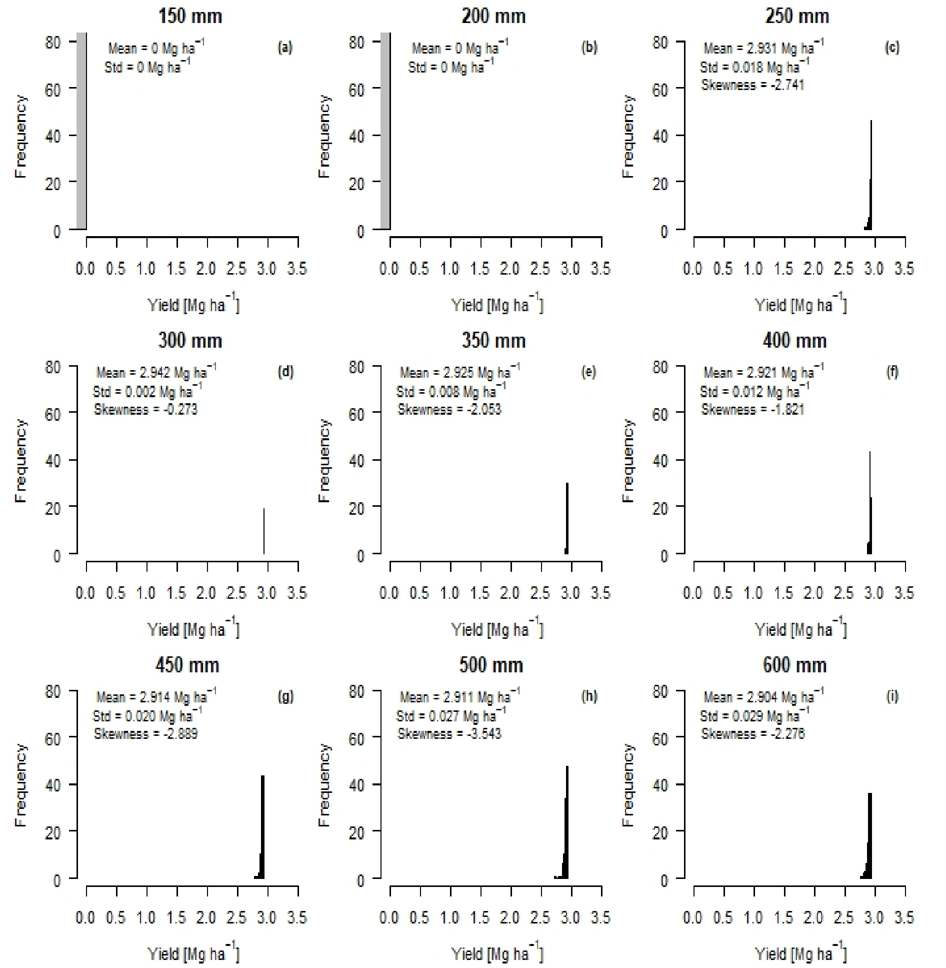


Figure B.1. Scenario 1

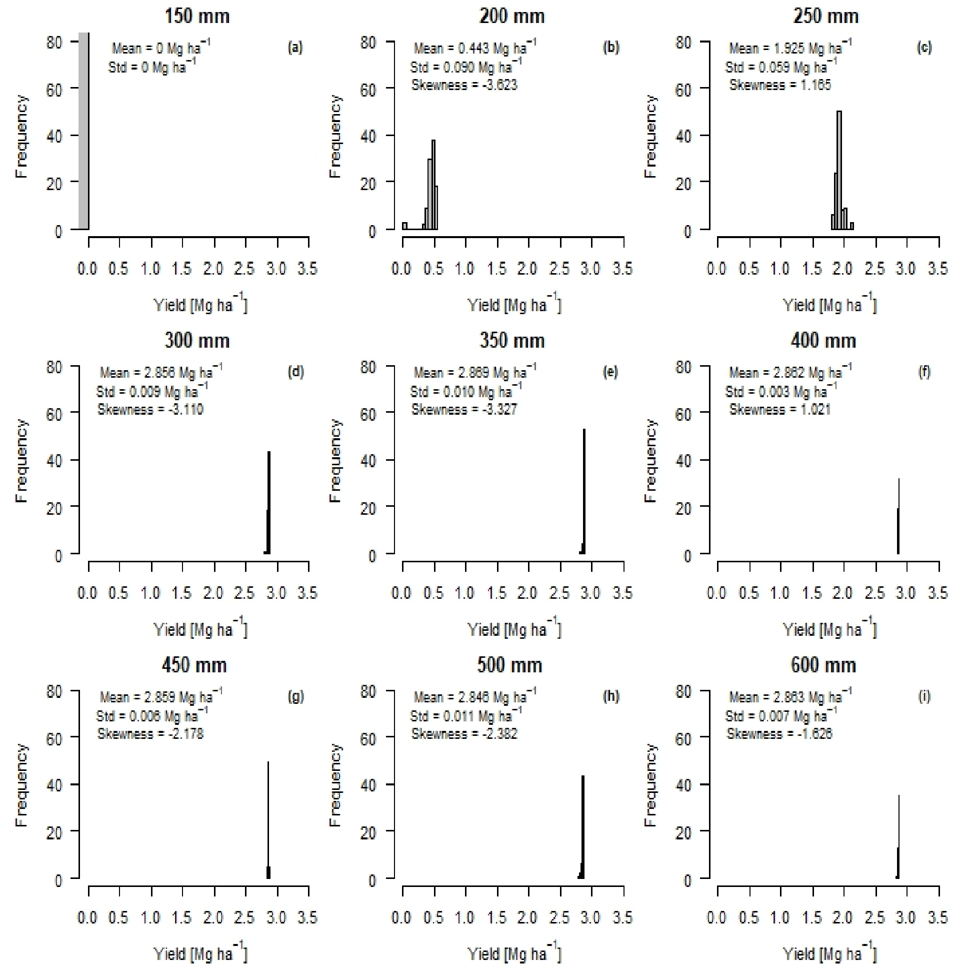
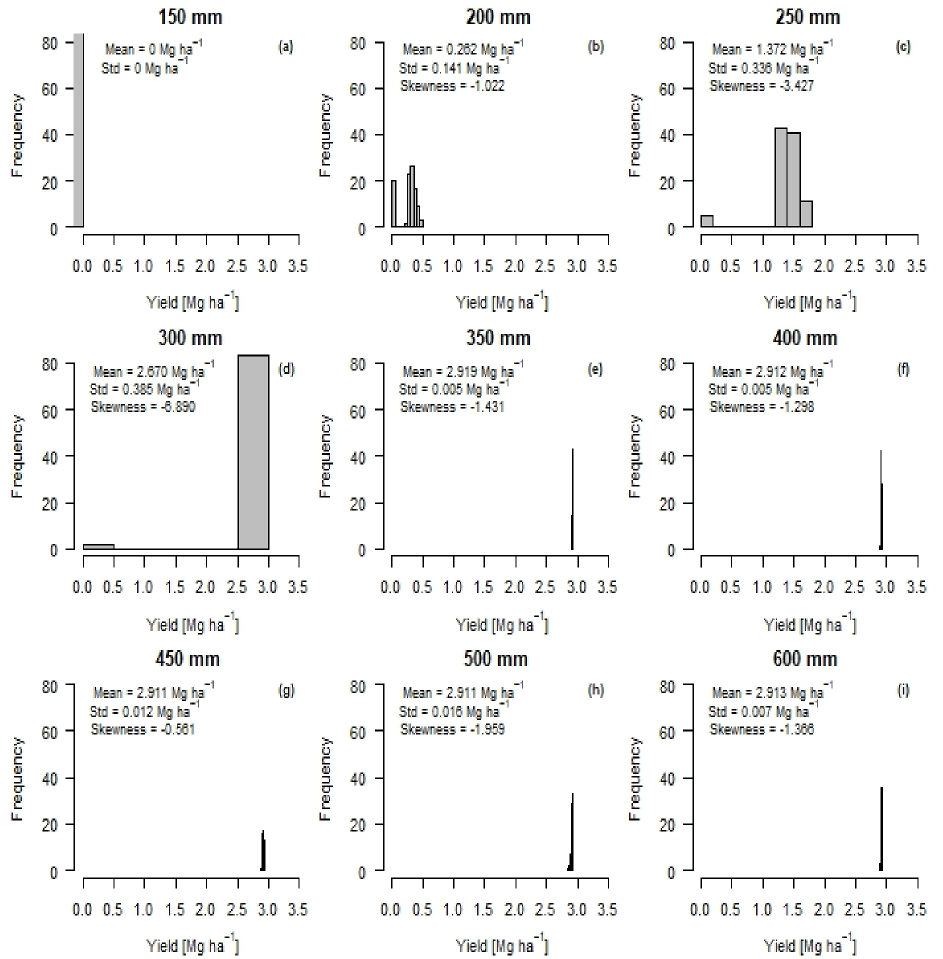


Figure B.2. Scenario 2



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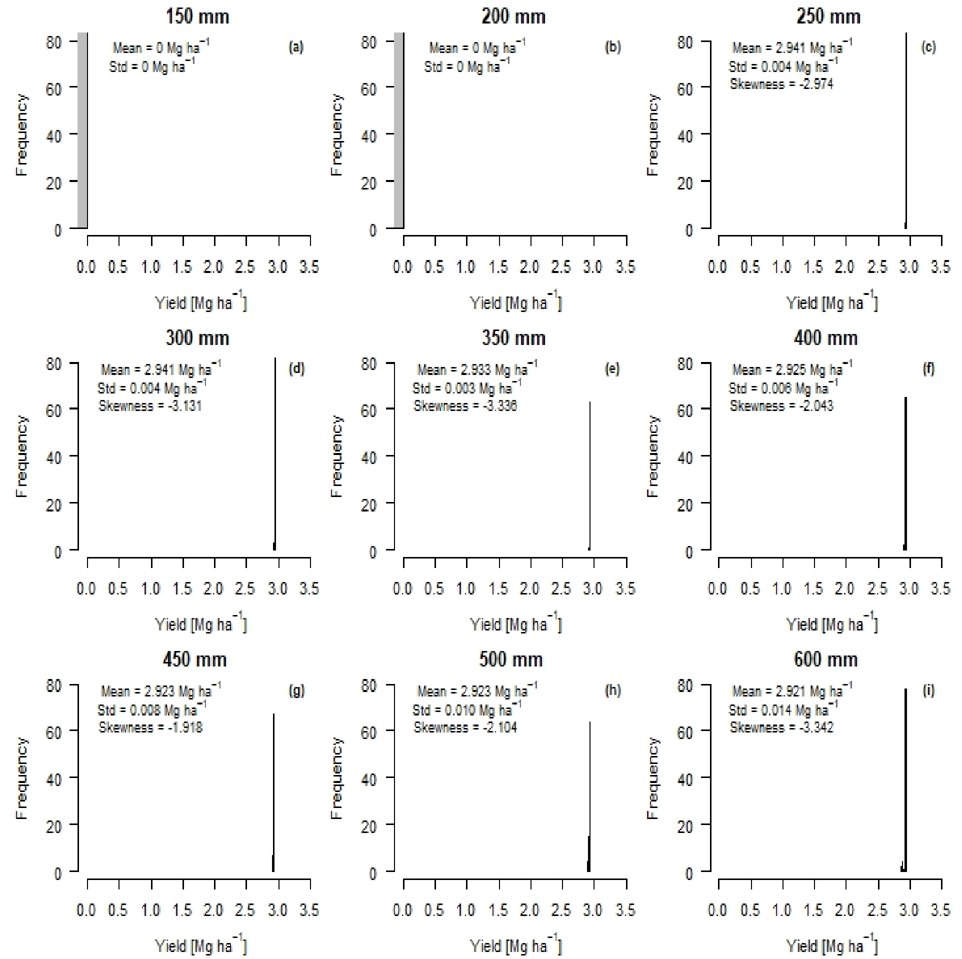


Figure B.4. Scenario 4

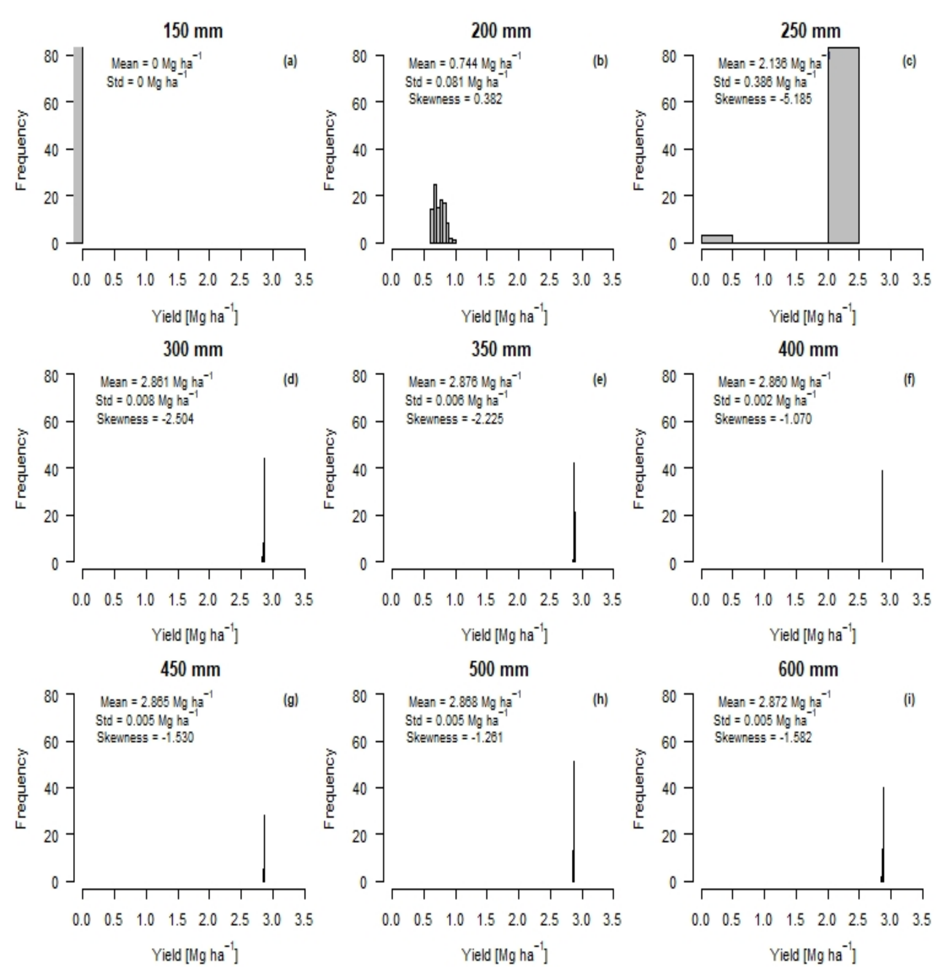
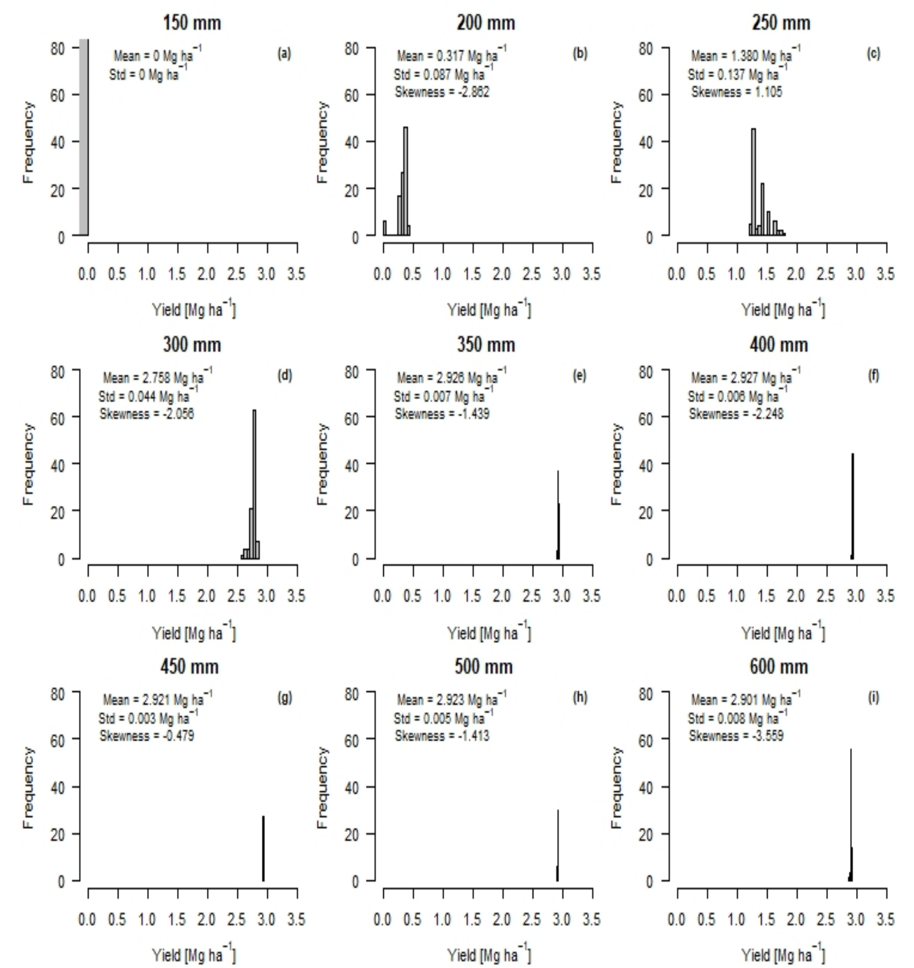


Figure B.5. Scenario 5



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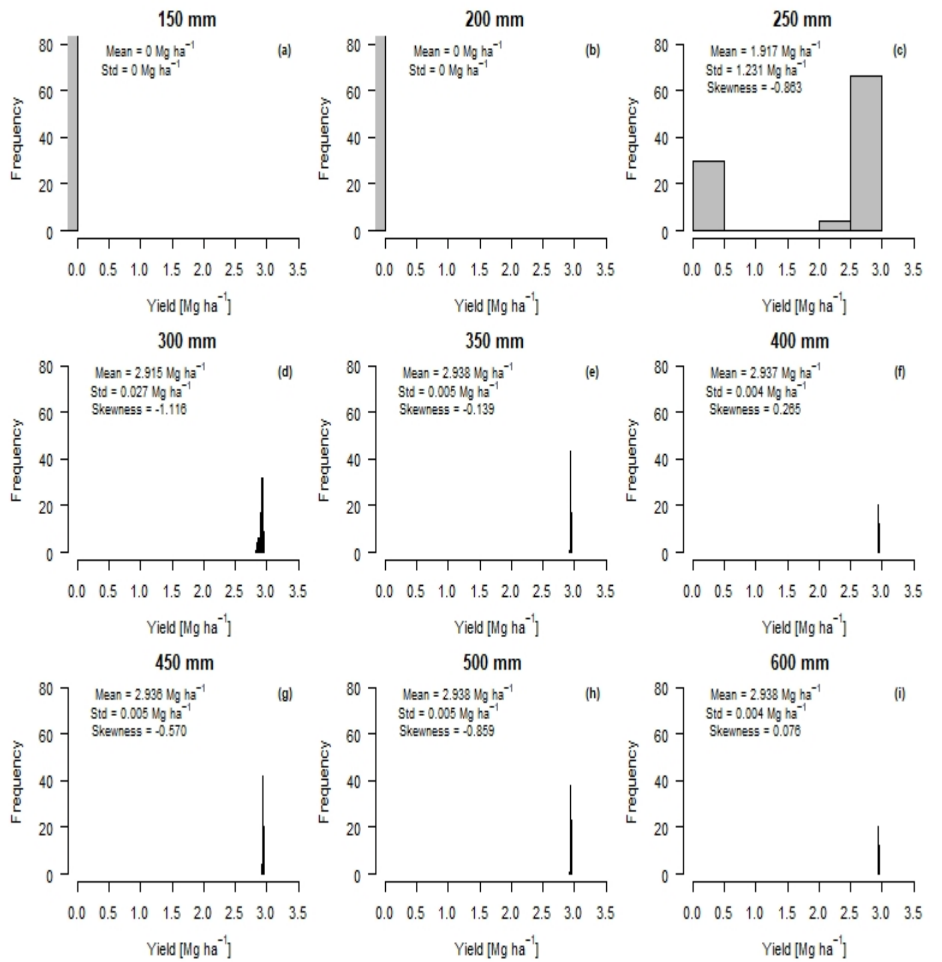


Figure B.7. Scenario 7

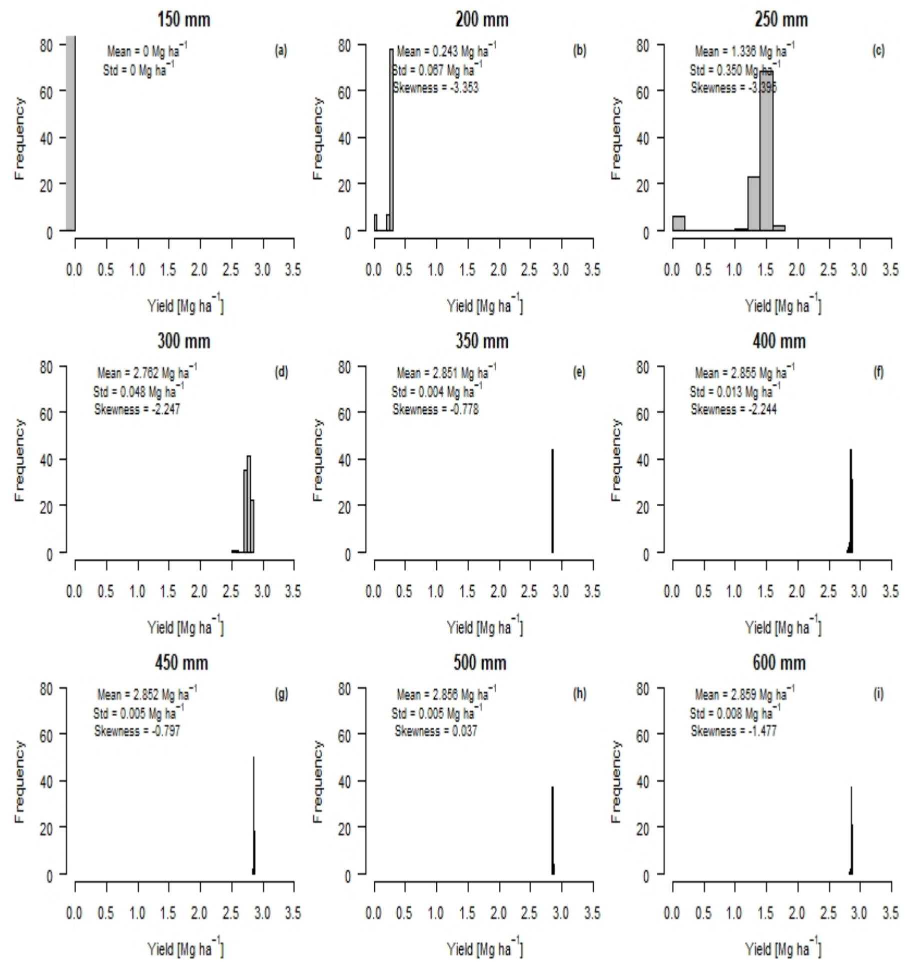


Figure B.8. Scenario 8

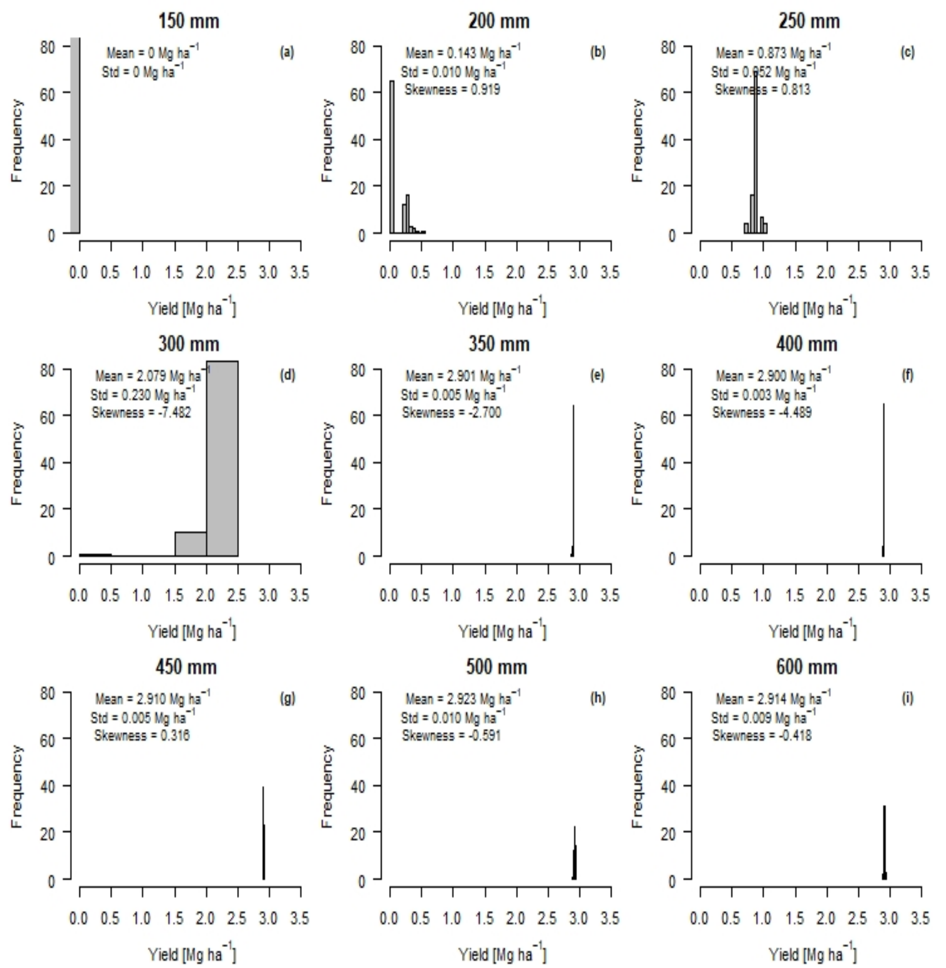


Figure B.9. Scenario 9

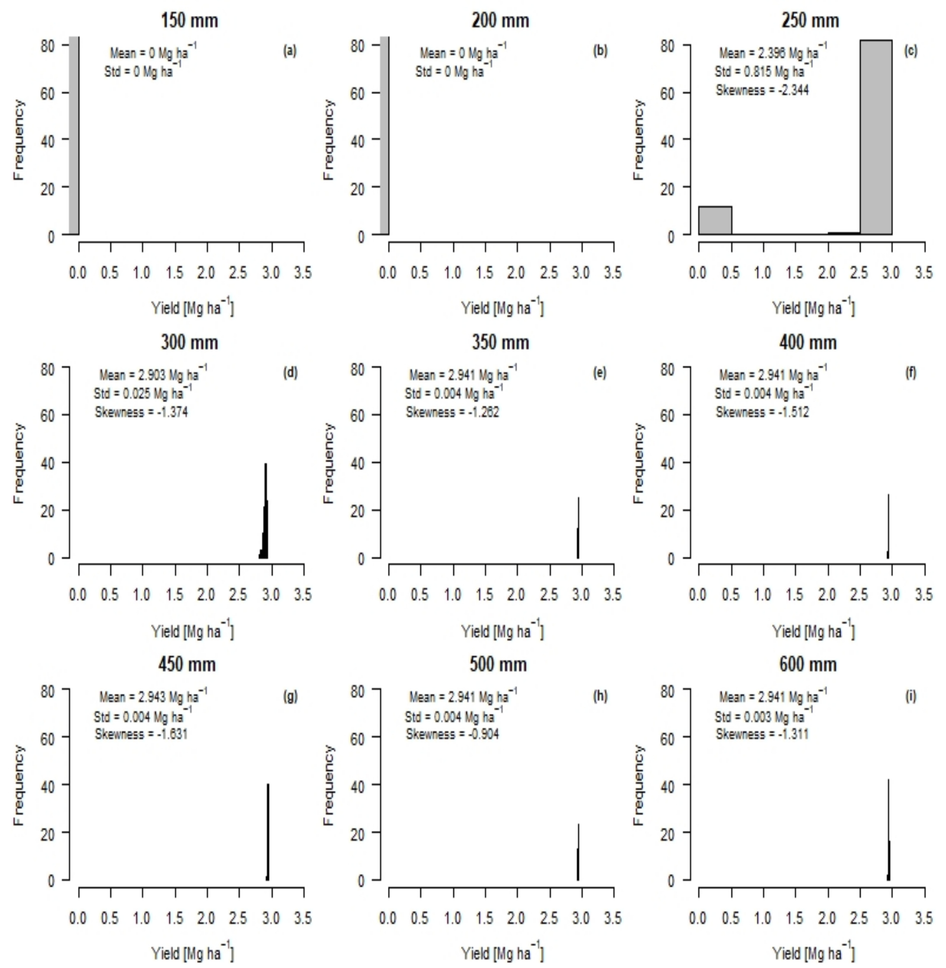


Figure B.10. Scenario 10

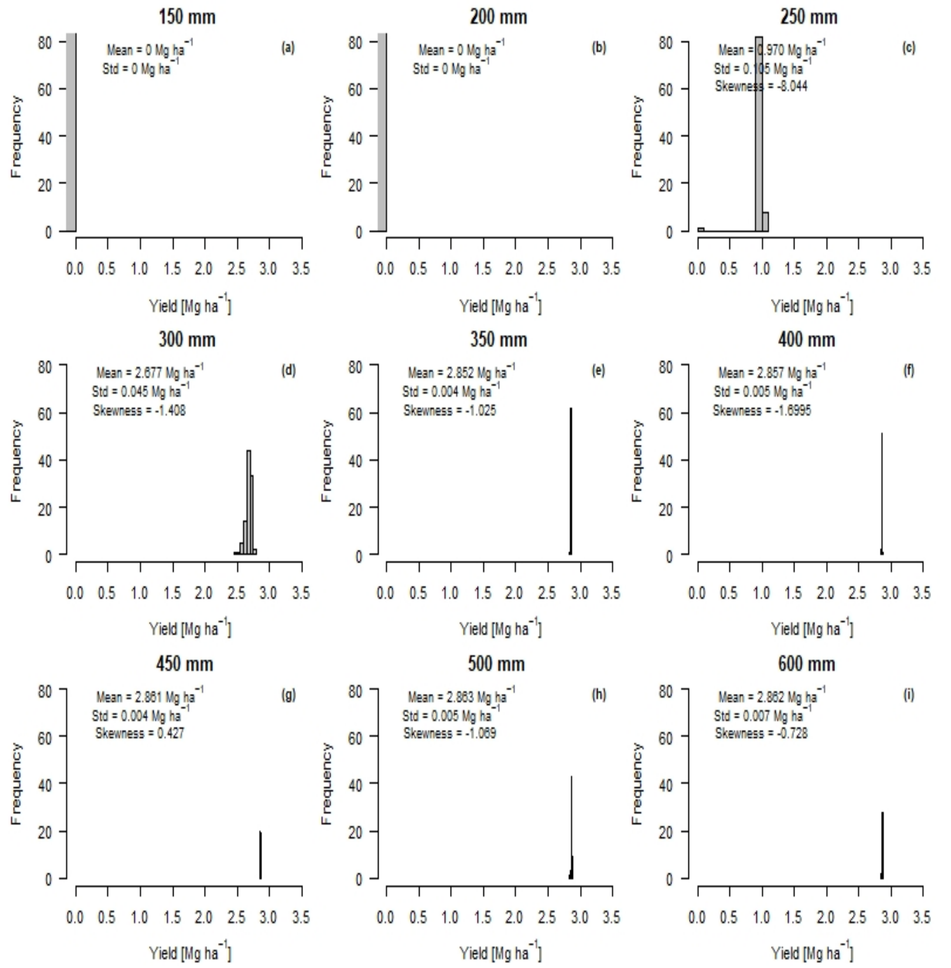
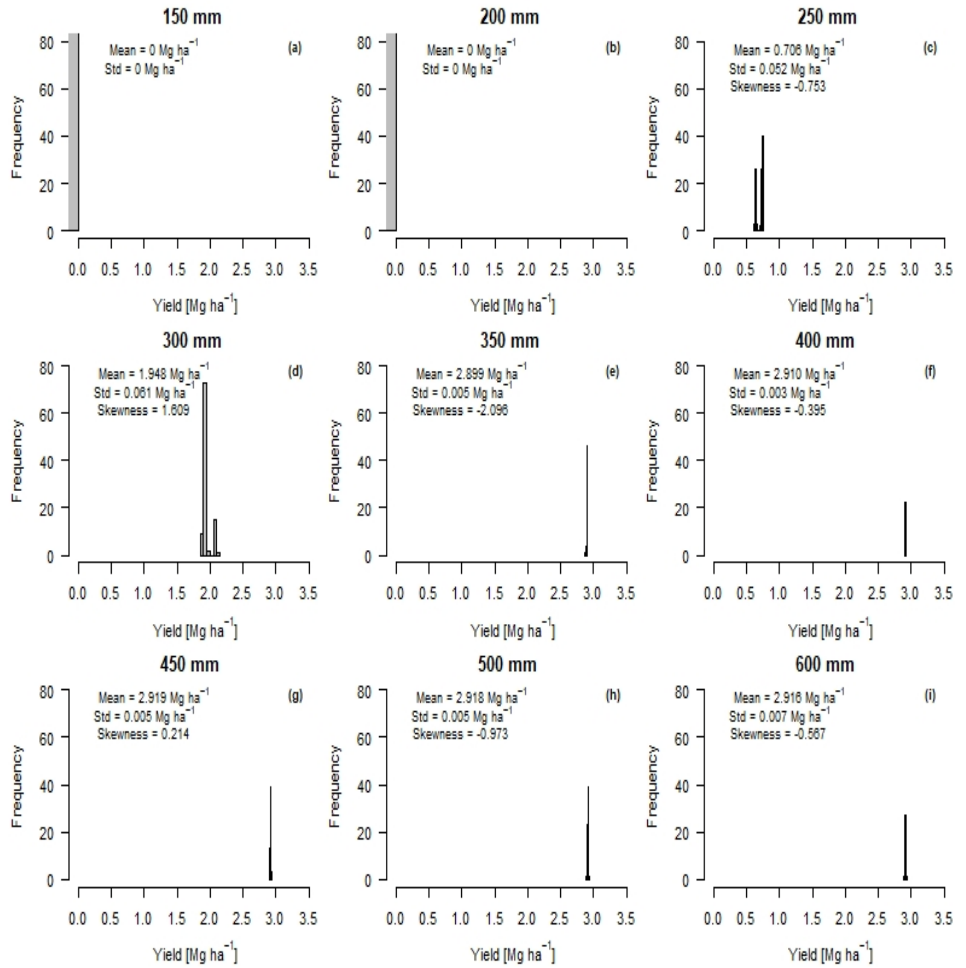


Figure B.11. Scenario 11



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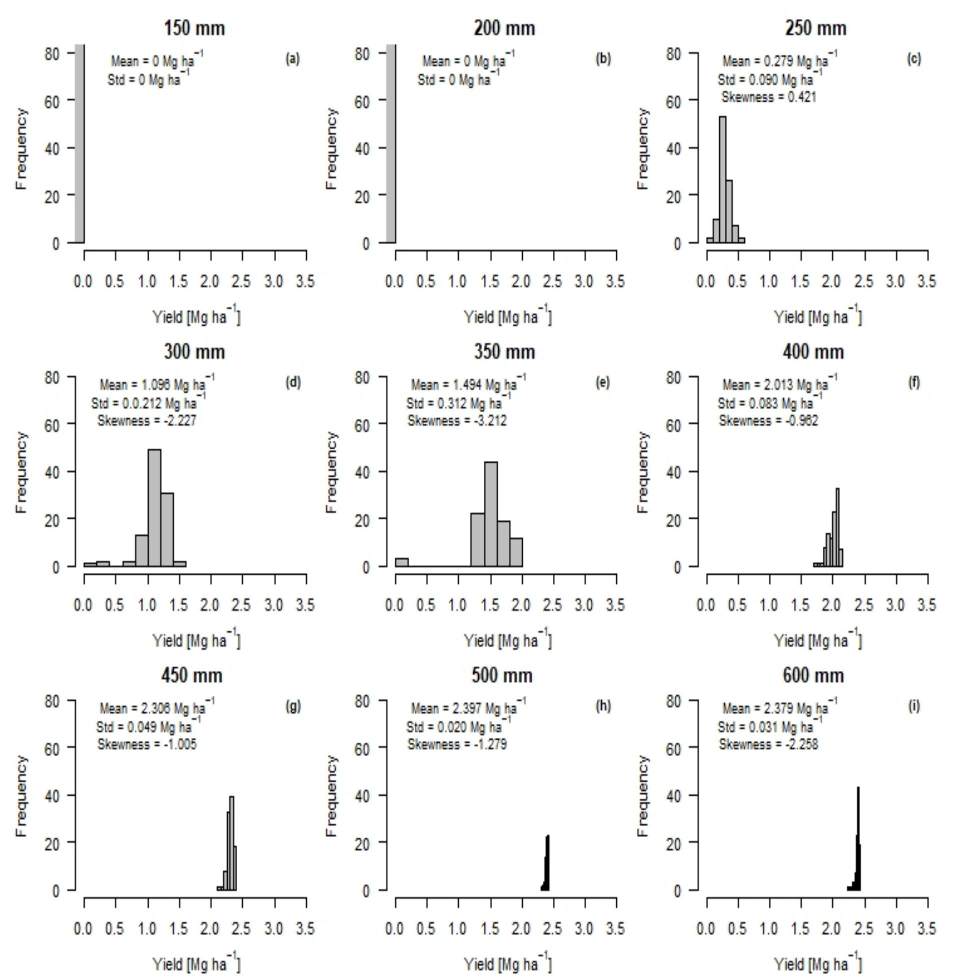

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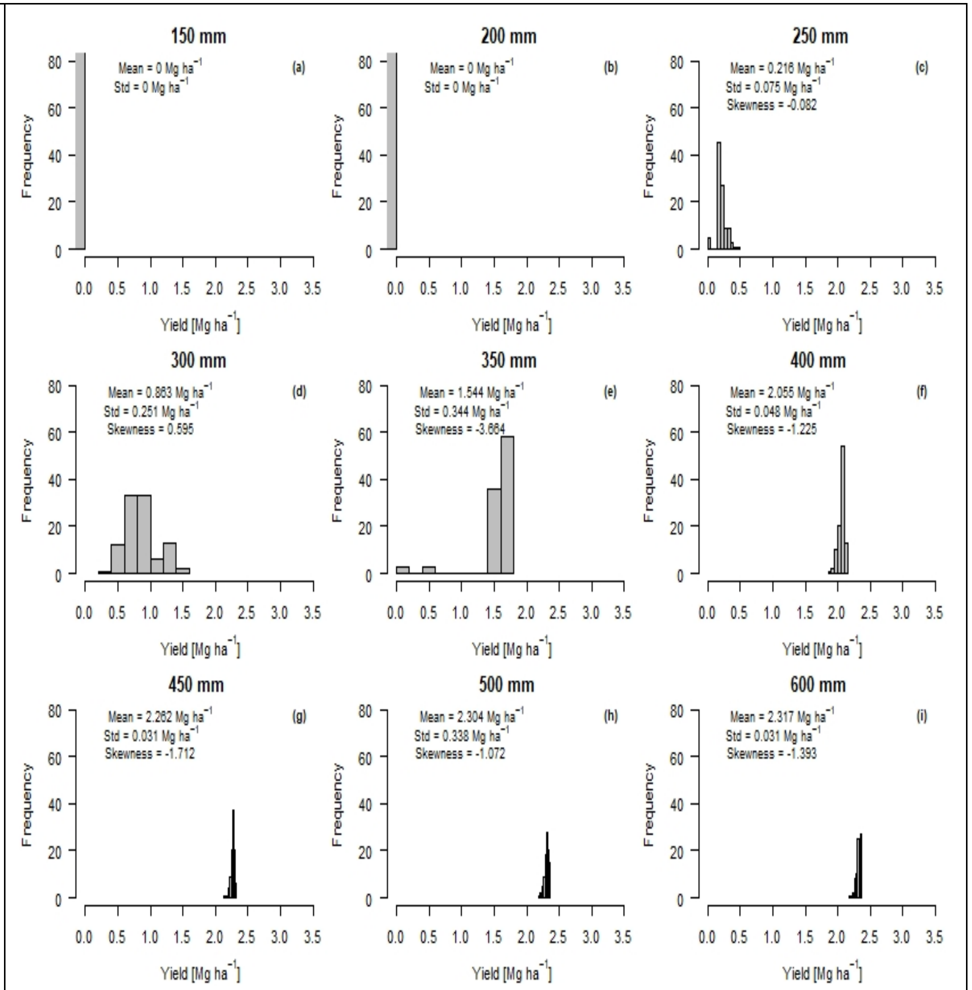
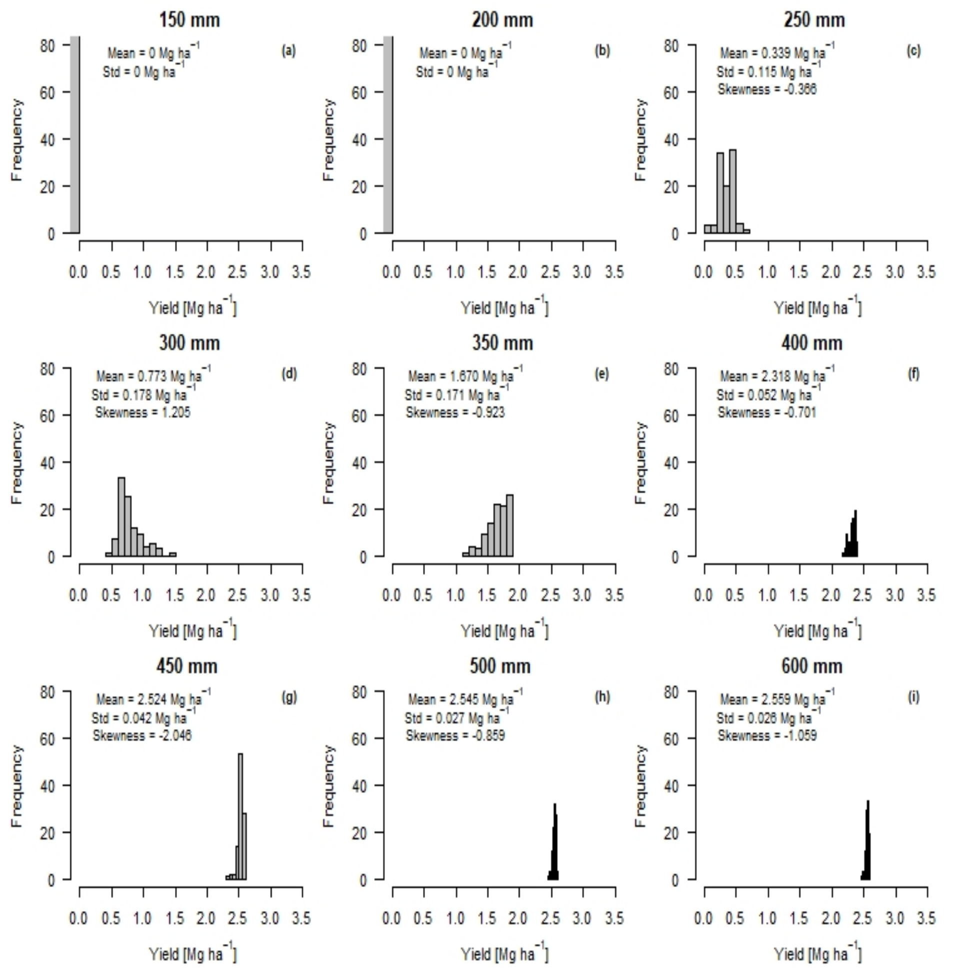


Figure B.14. Scenario 14



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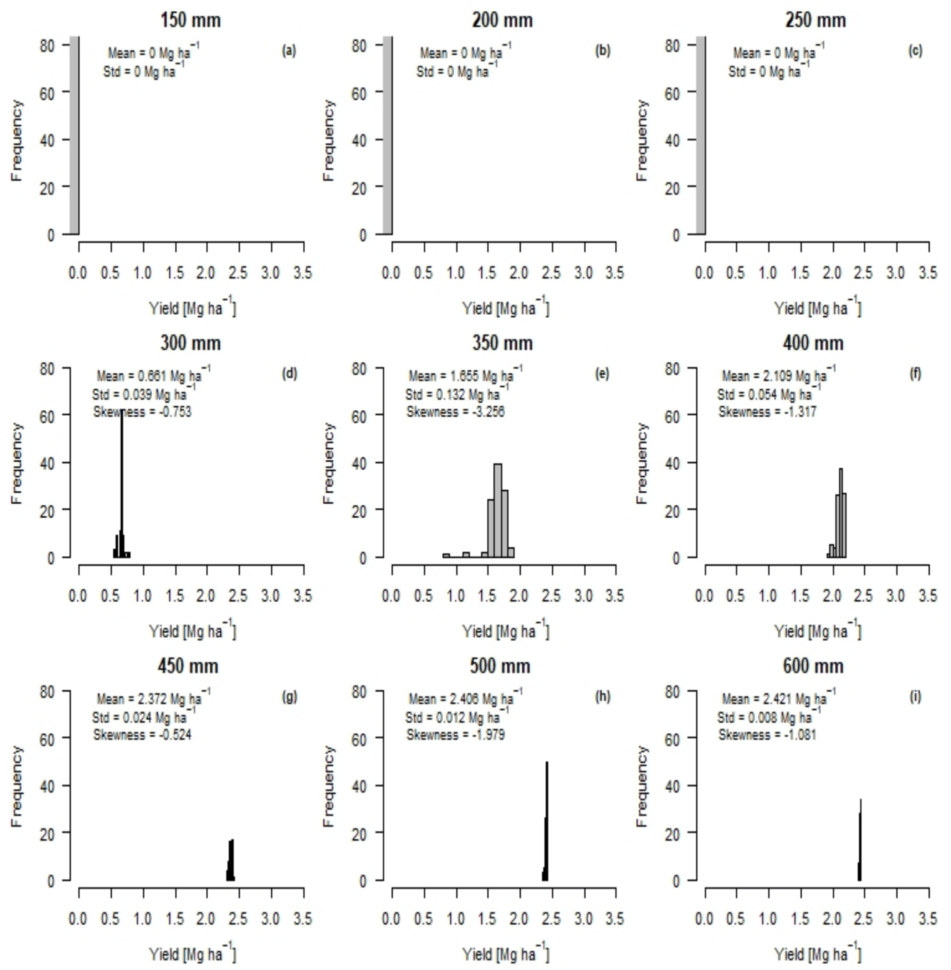
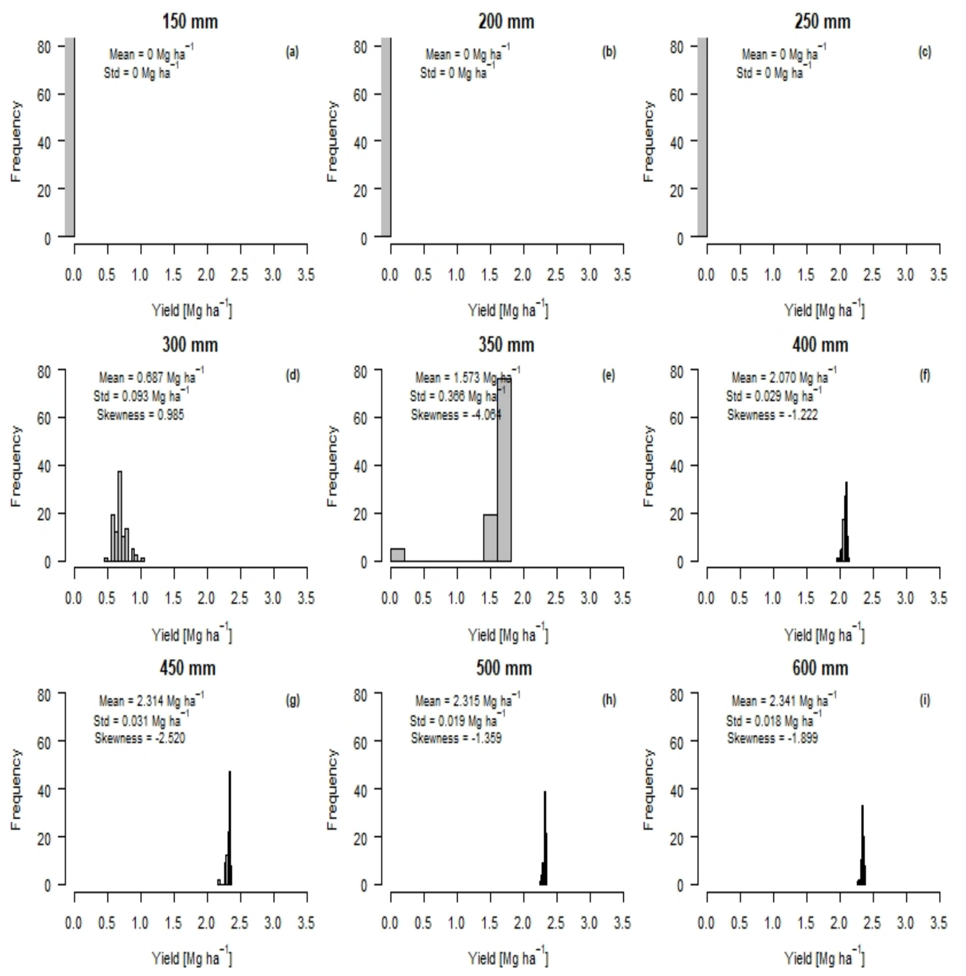


Figure B.16. Scenario 16



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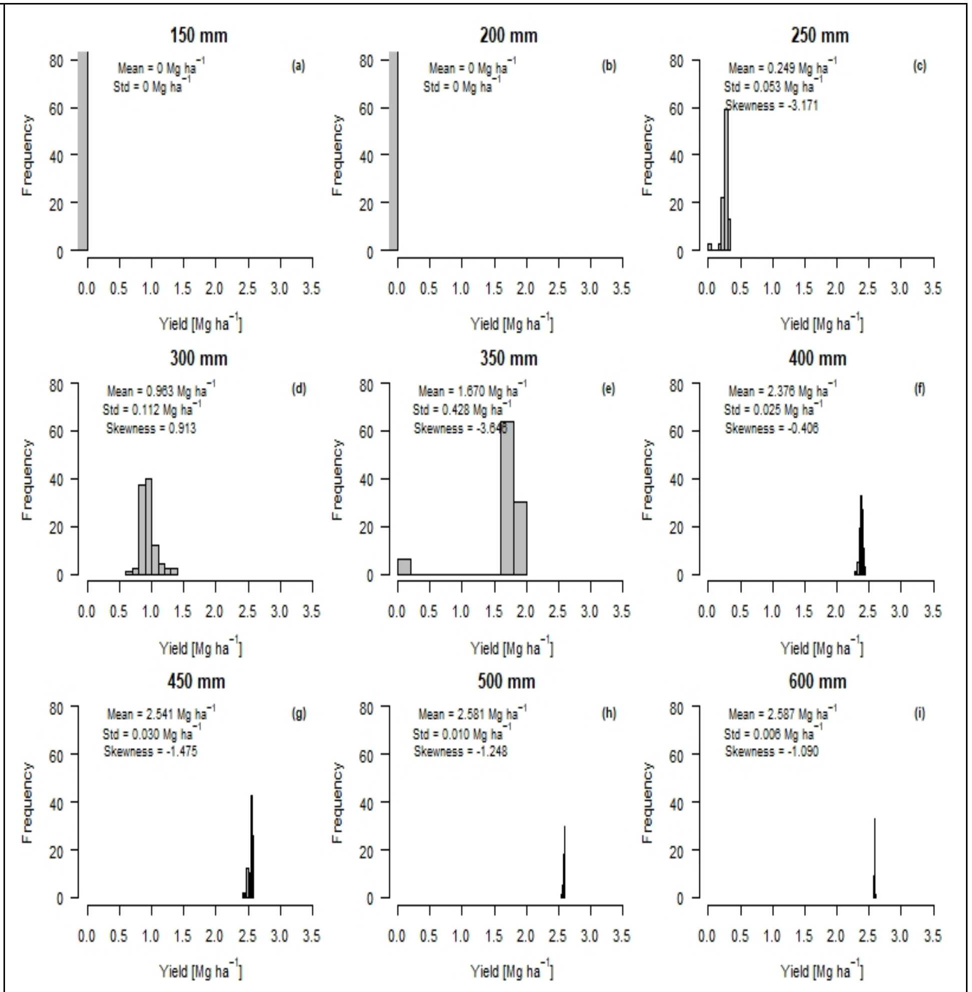
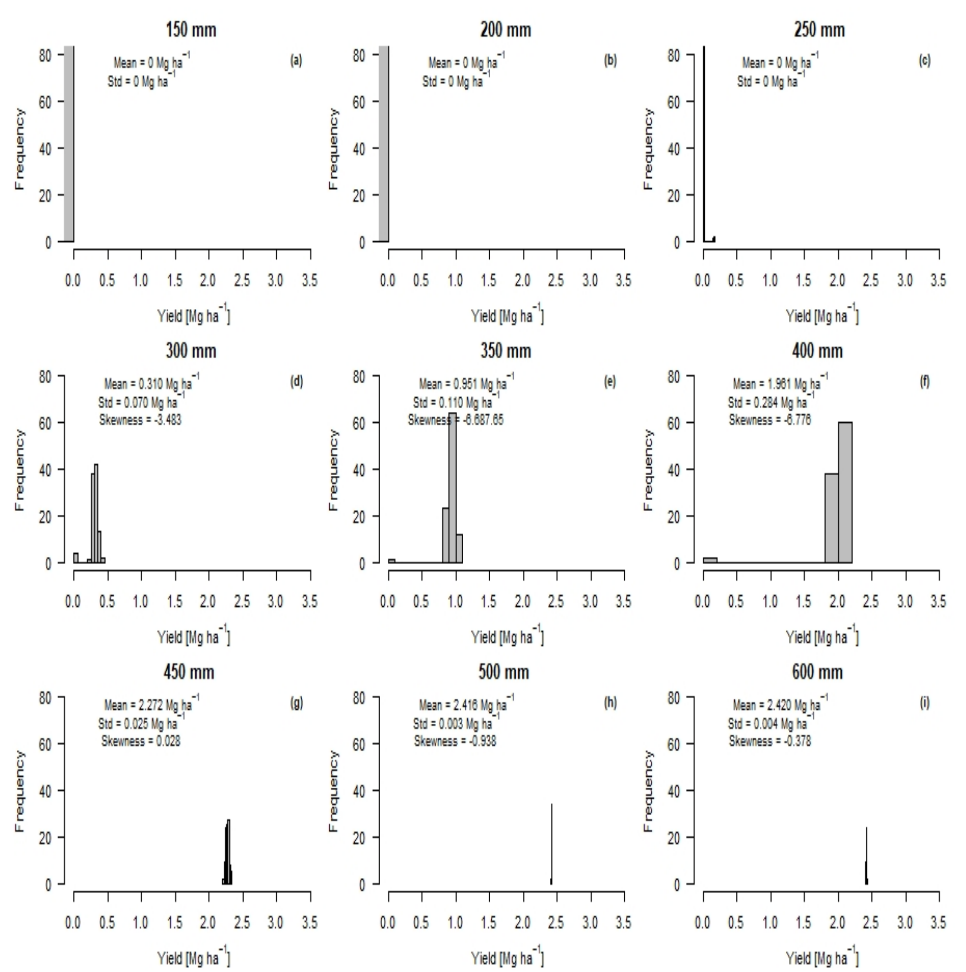


Figure B.18. Scenario 18



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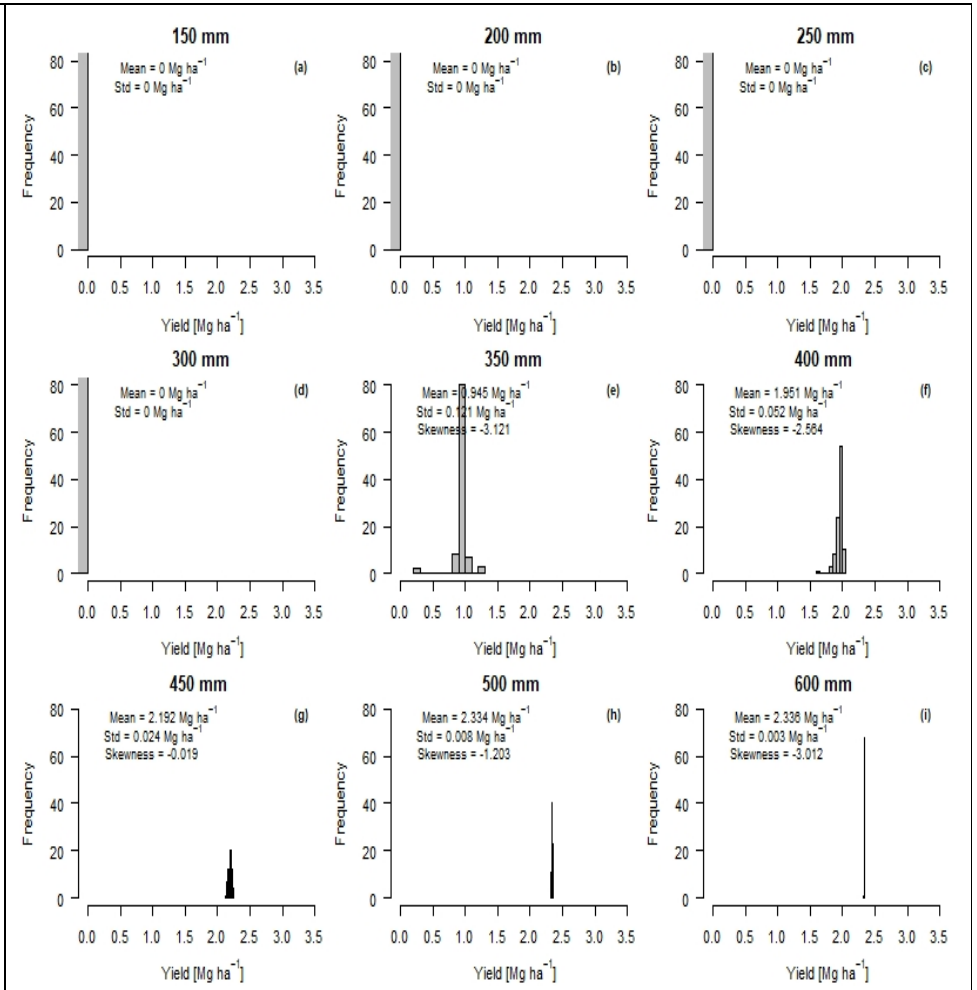

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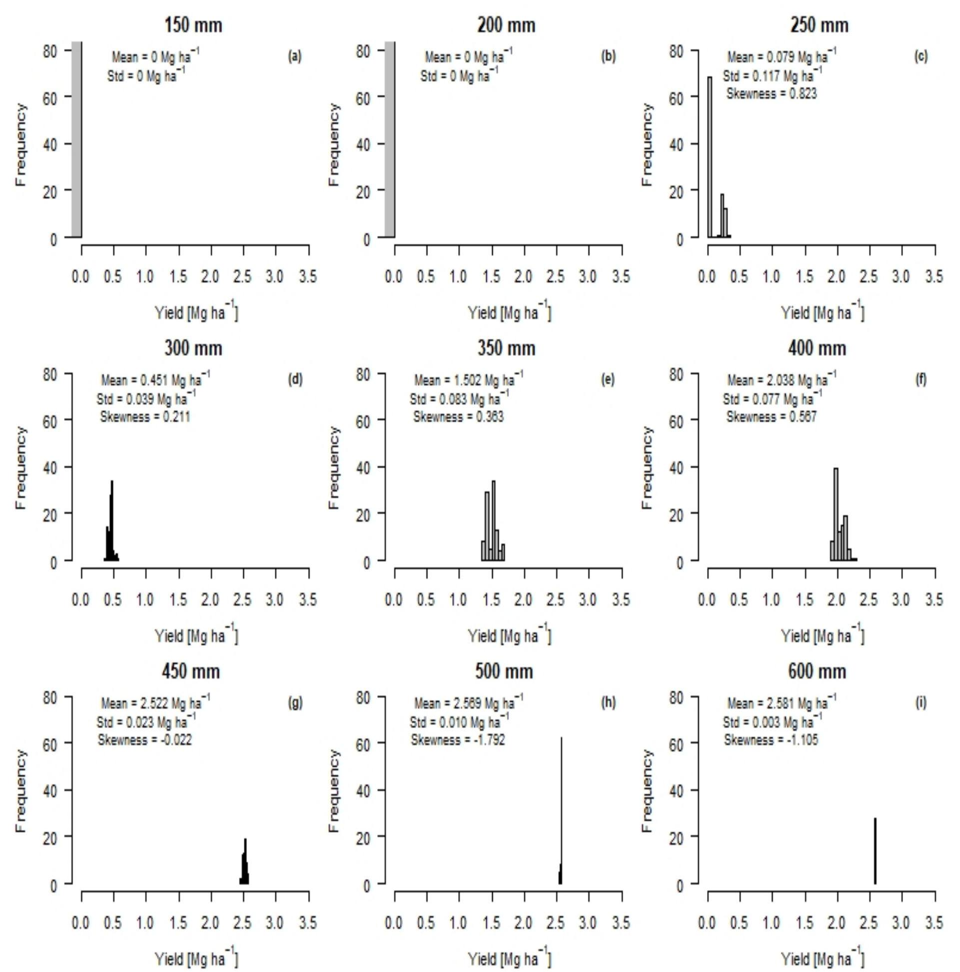

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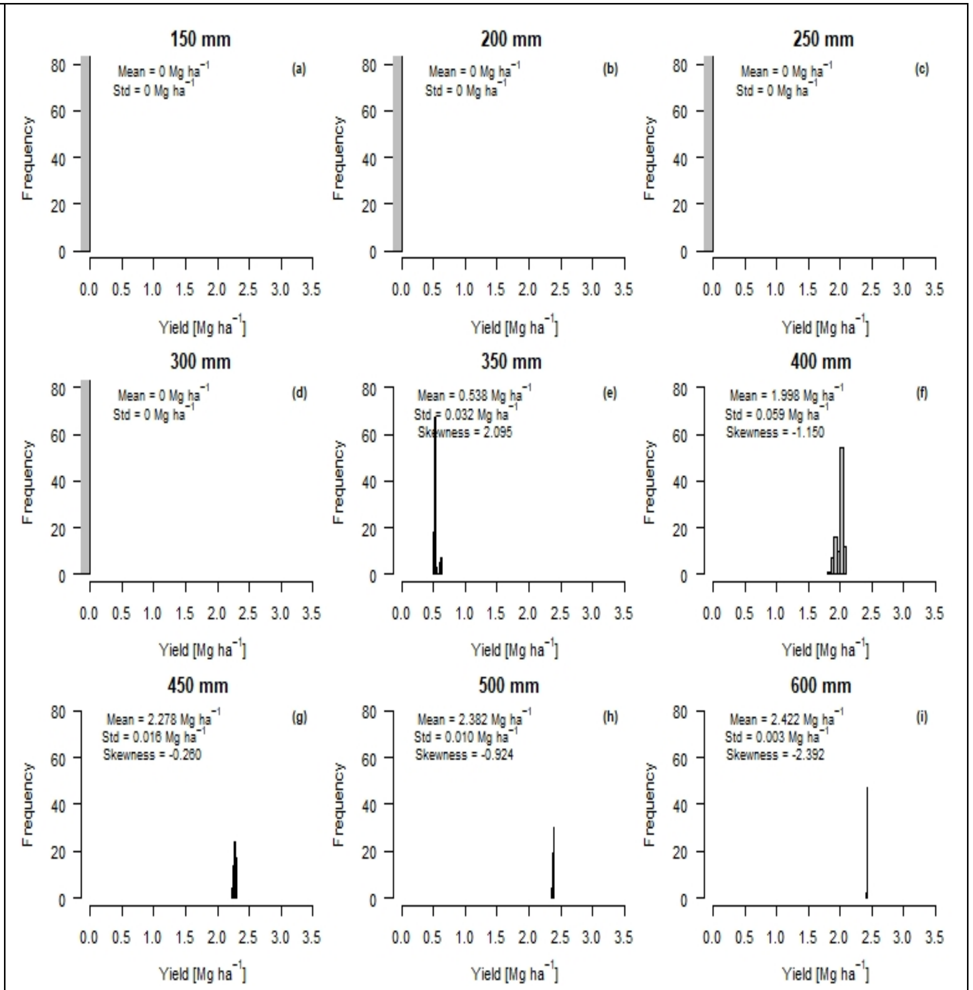

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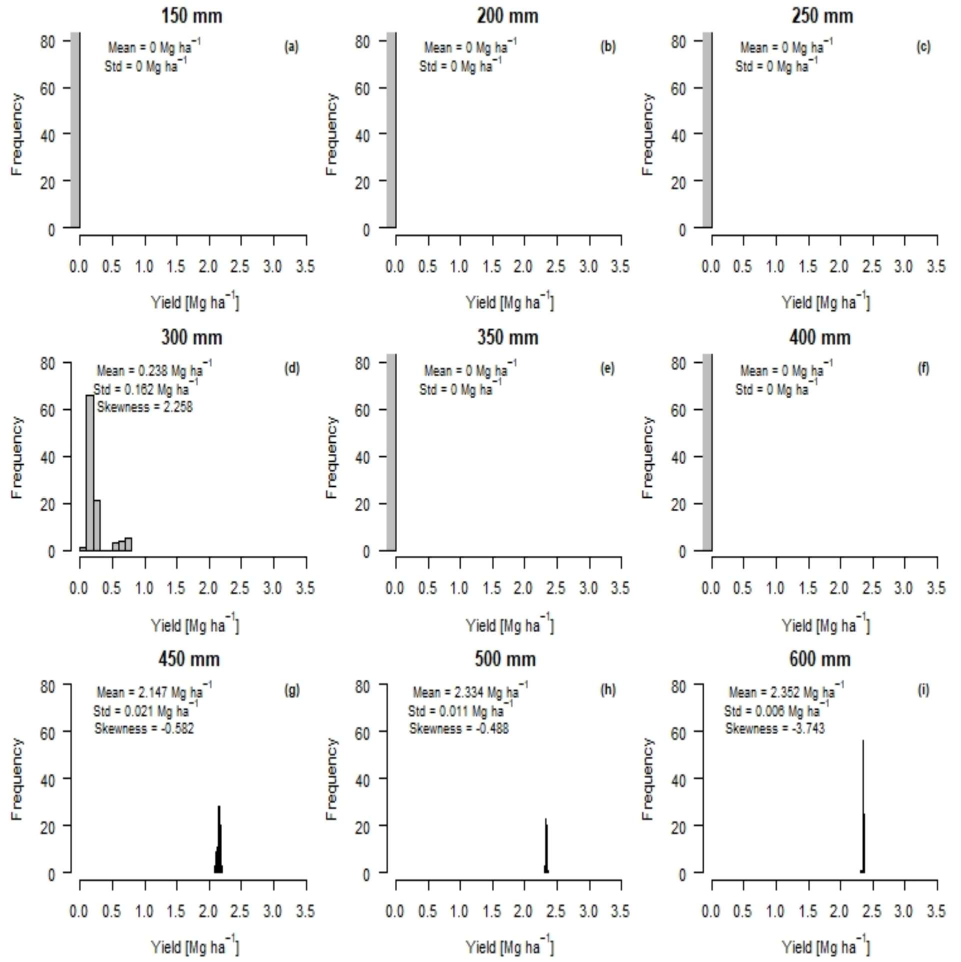

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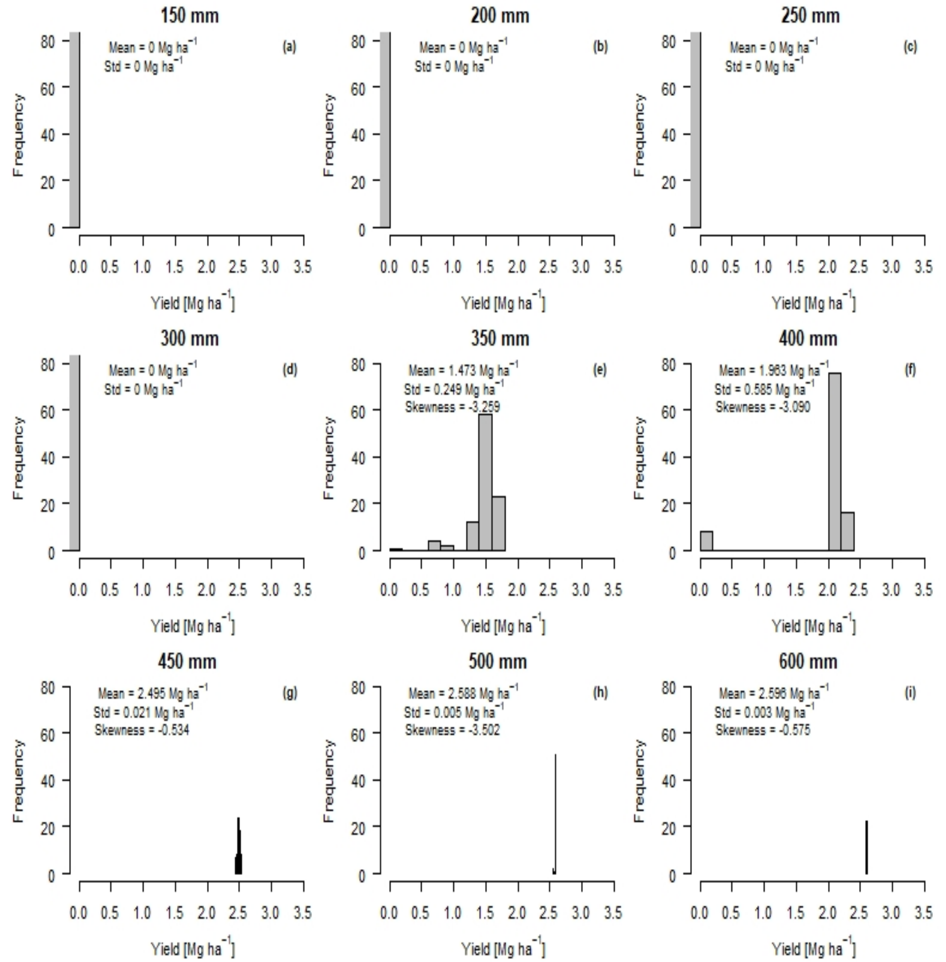

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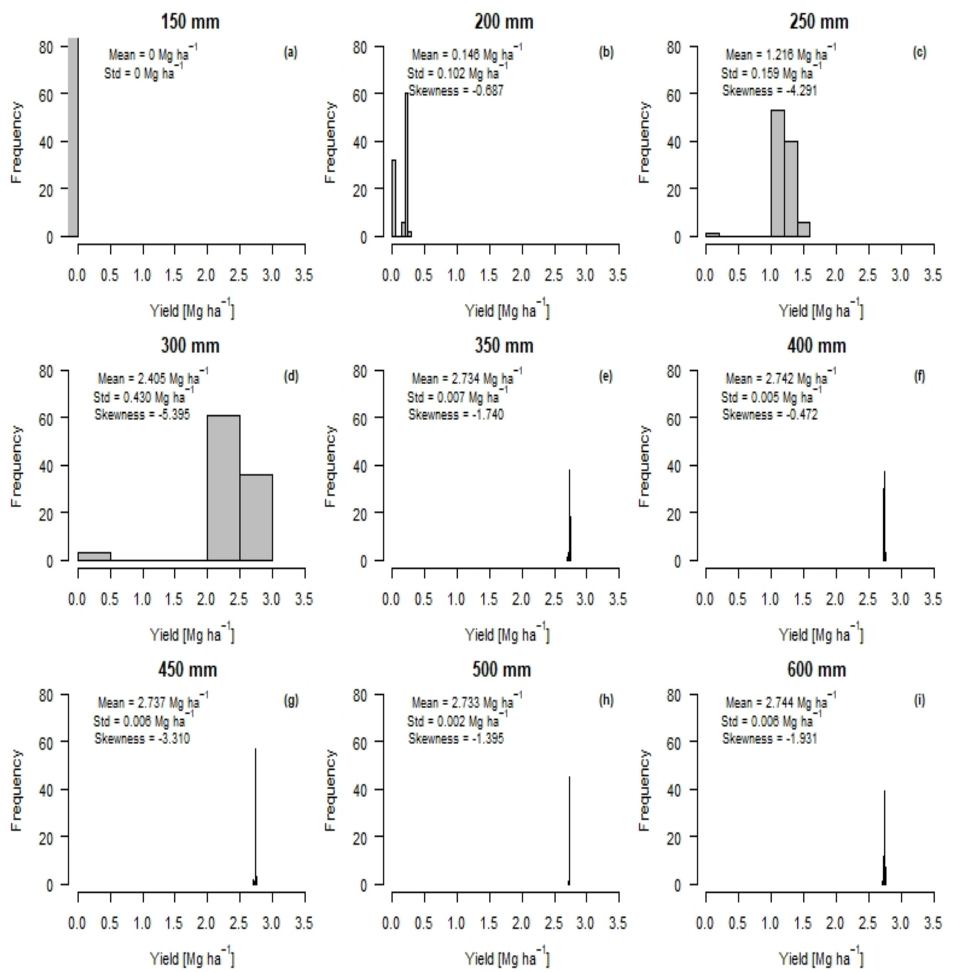

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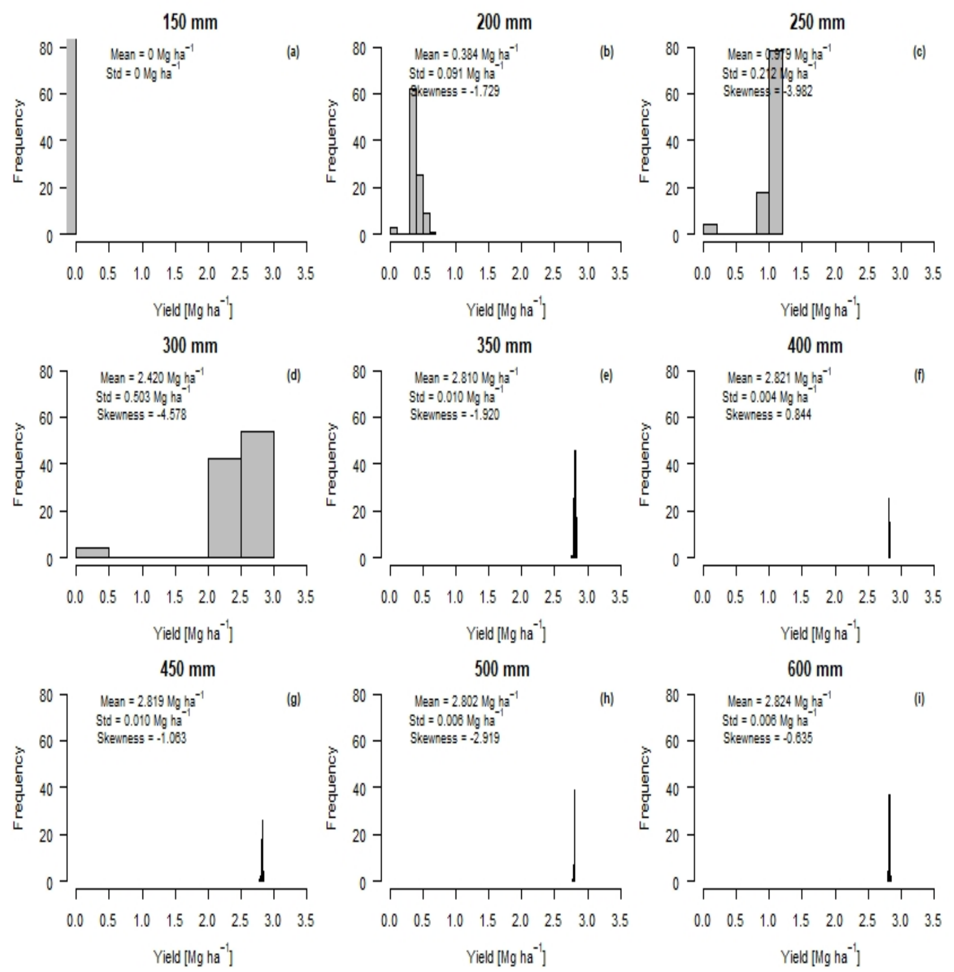

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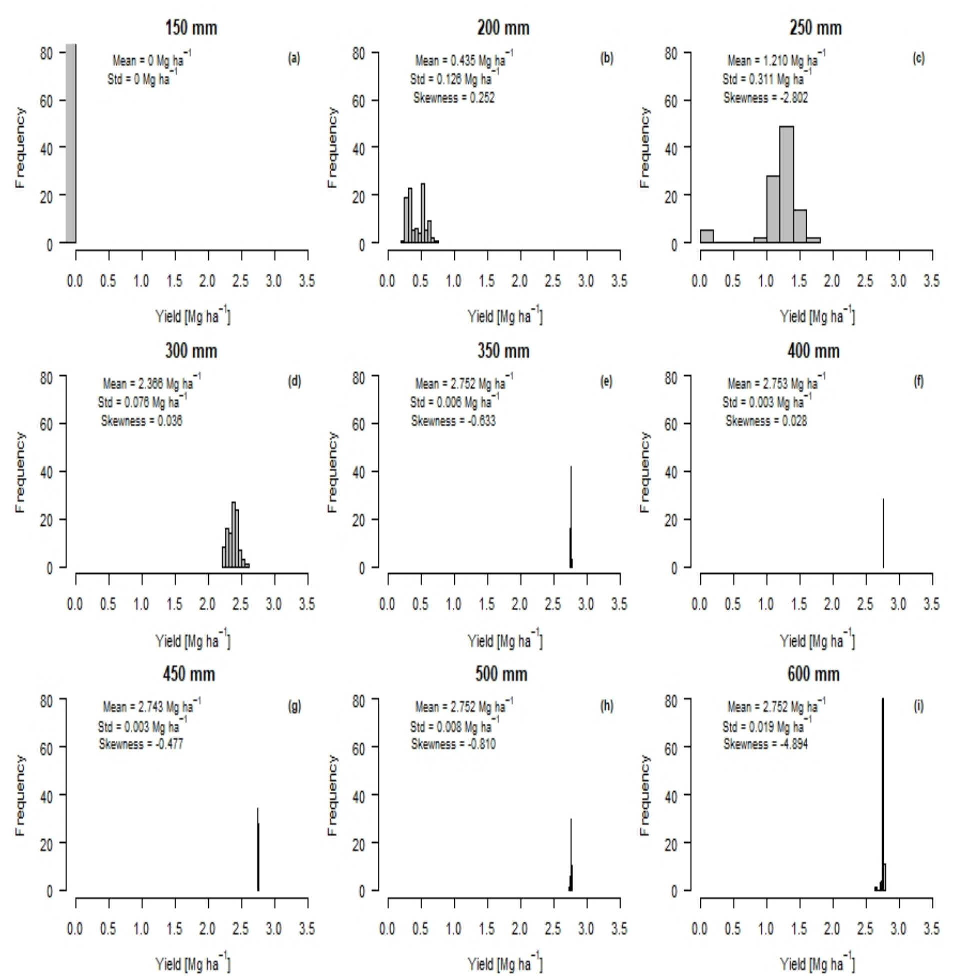

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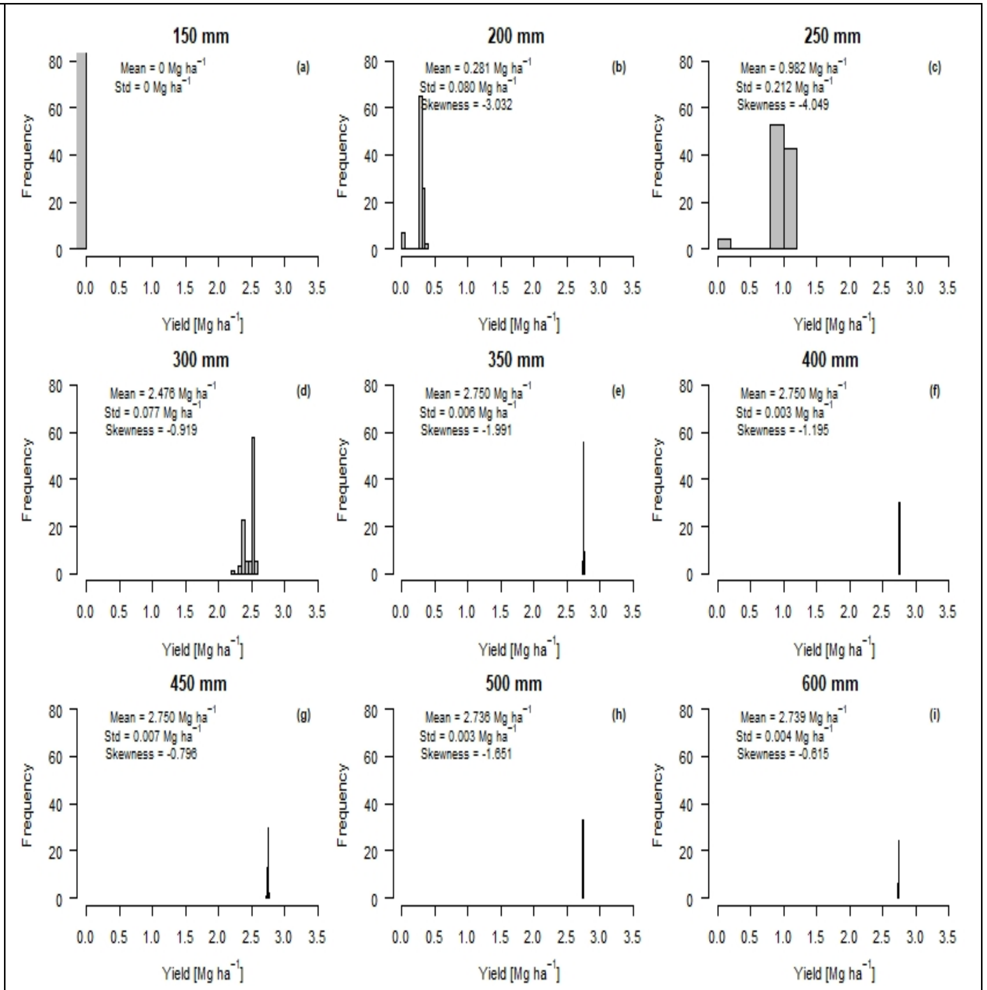

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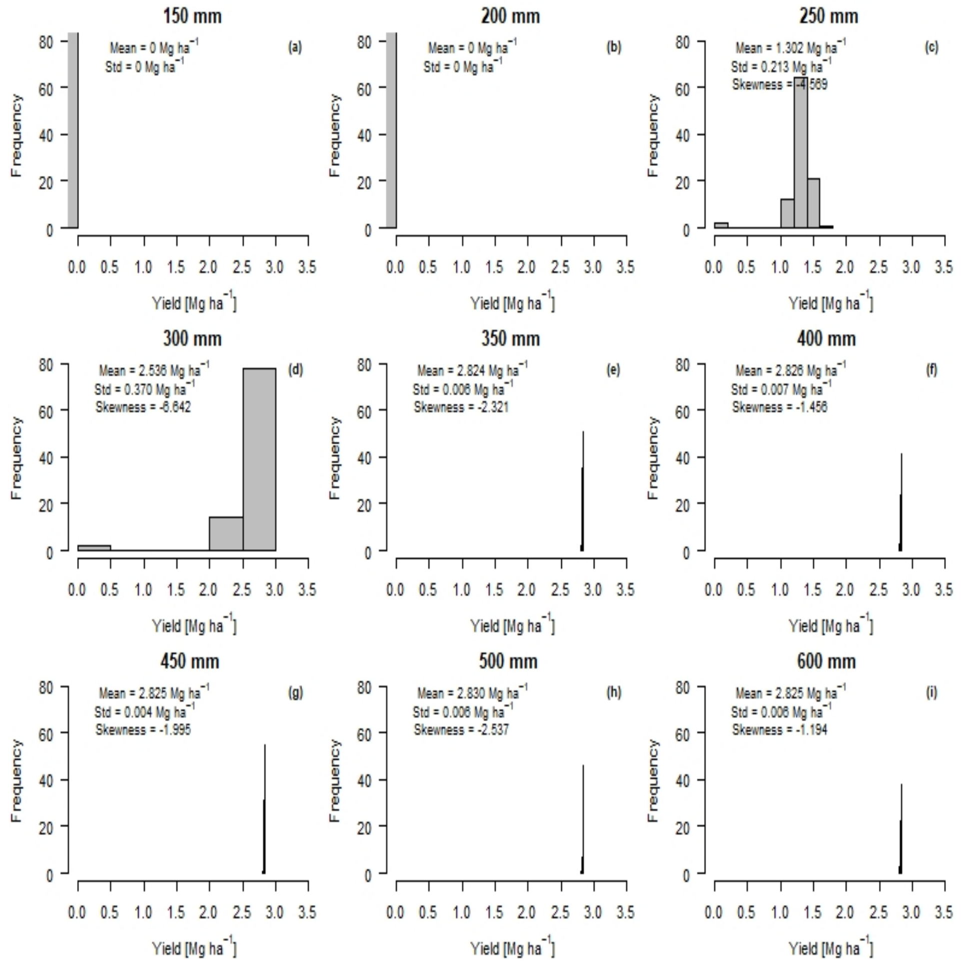

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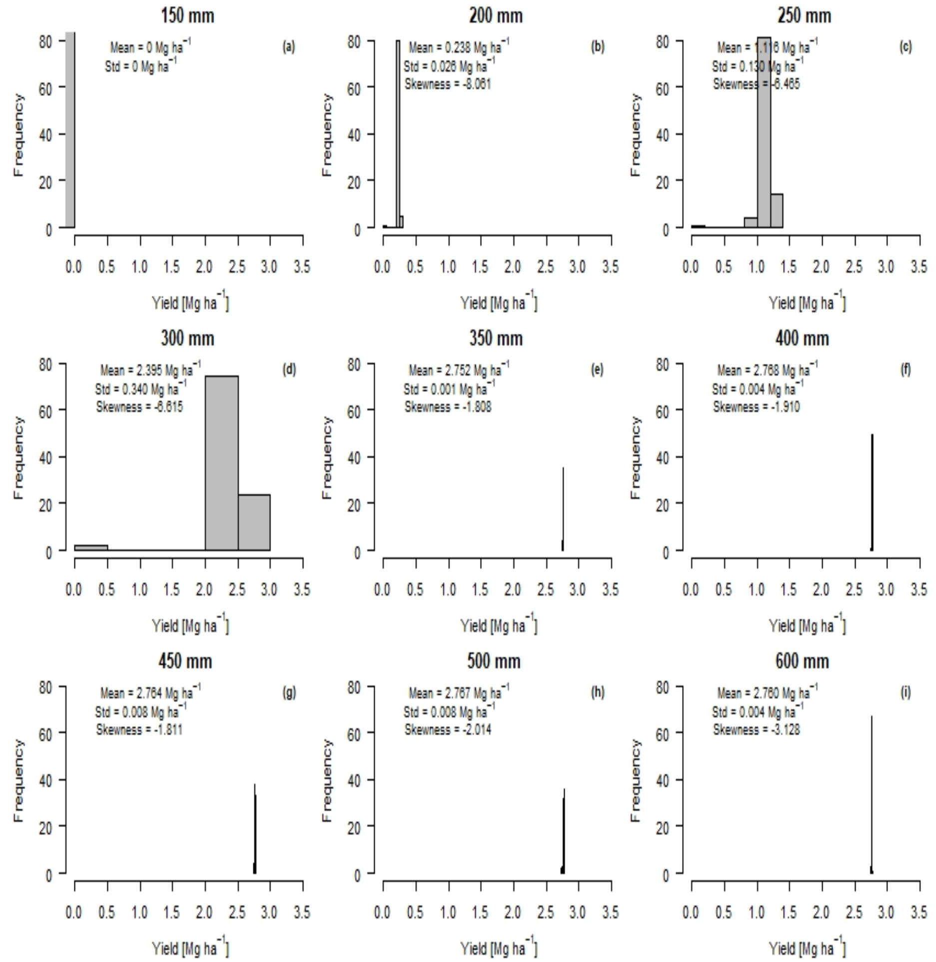

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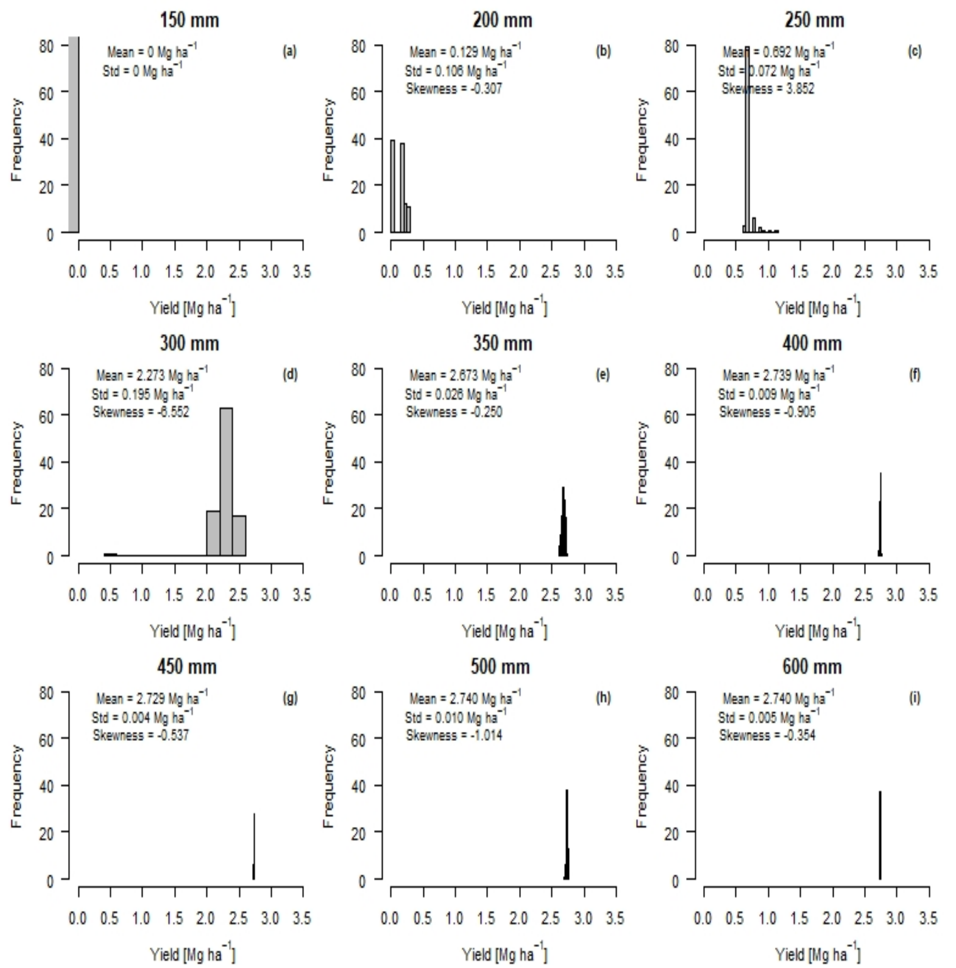

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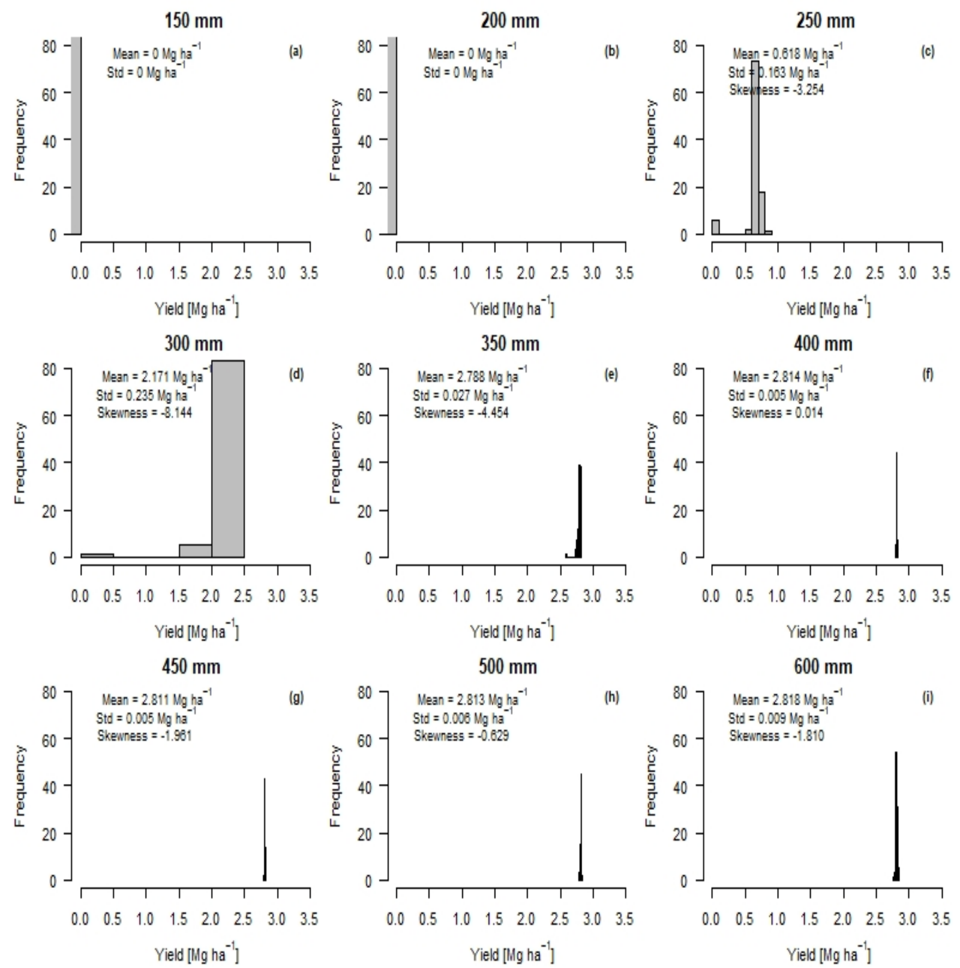

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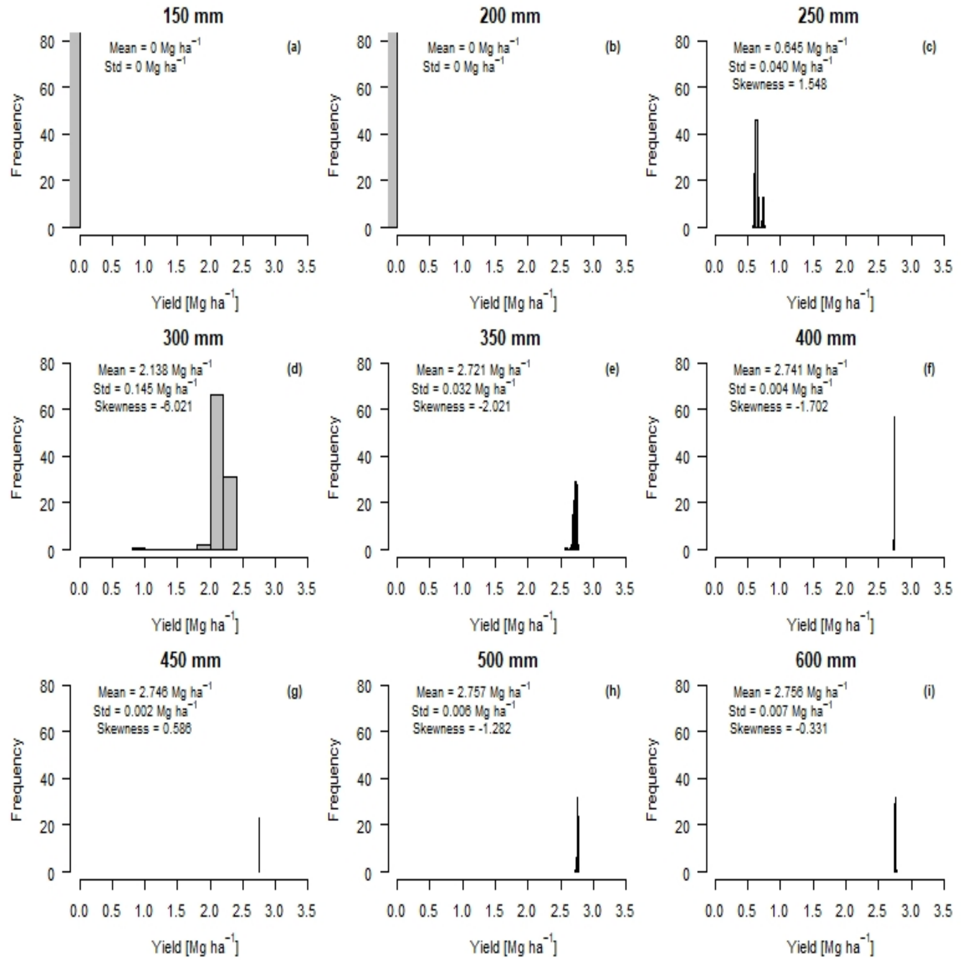

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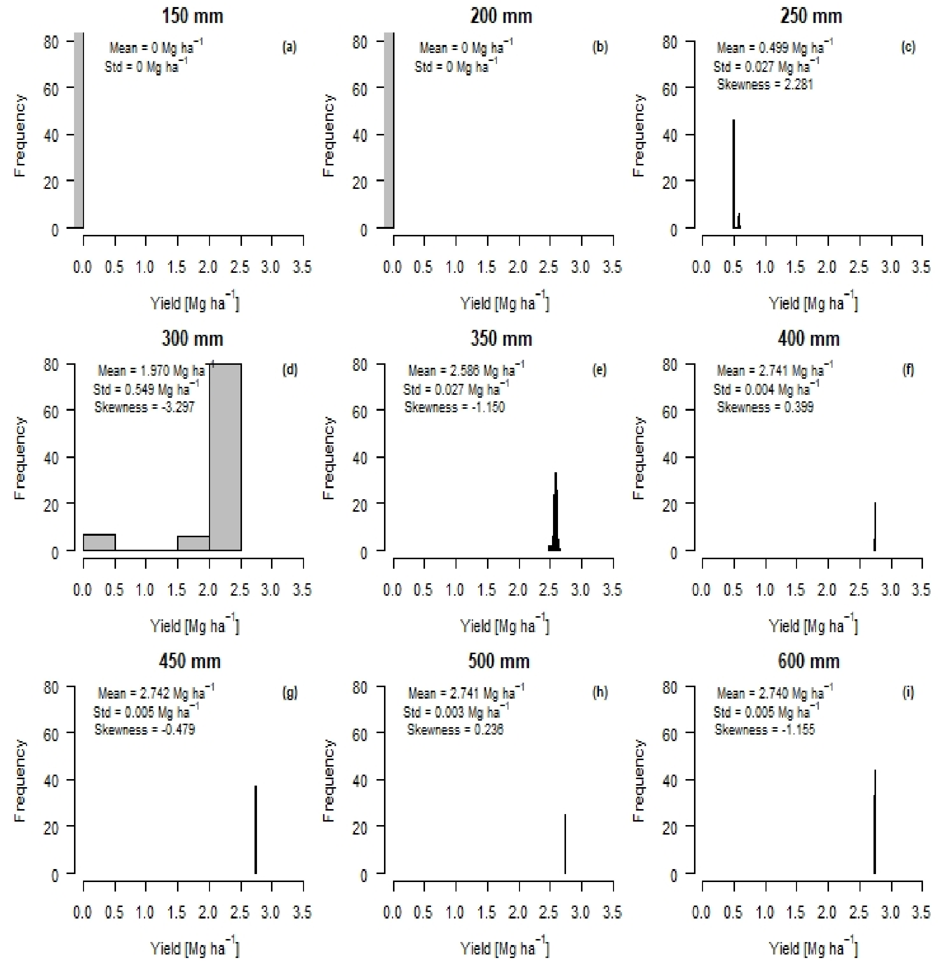

Figure B.34. Scenario 34

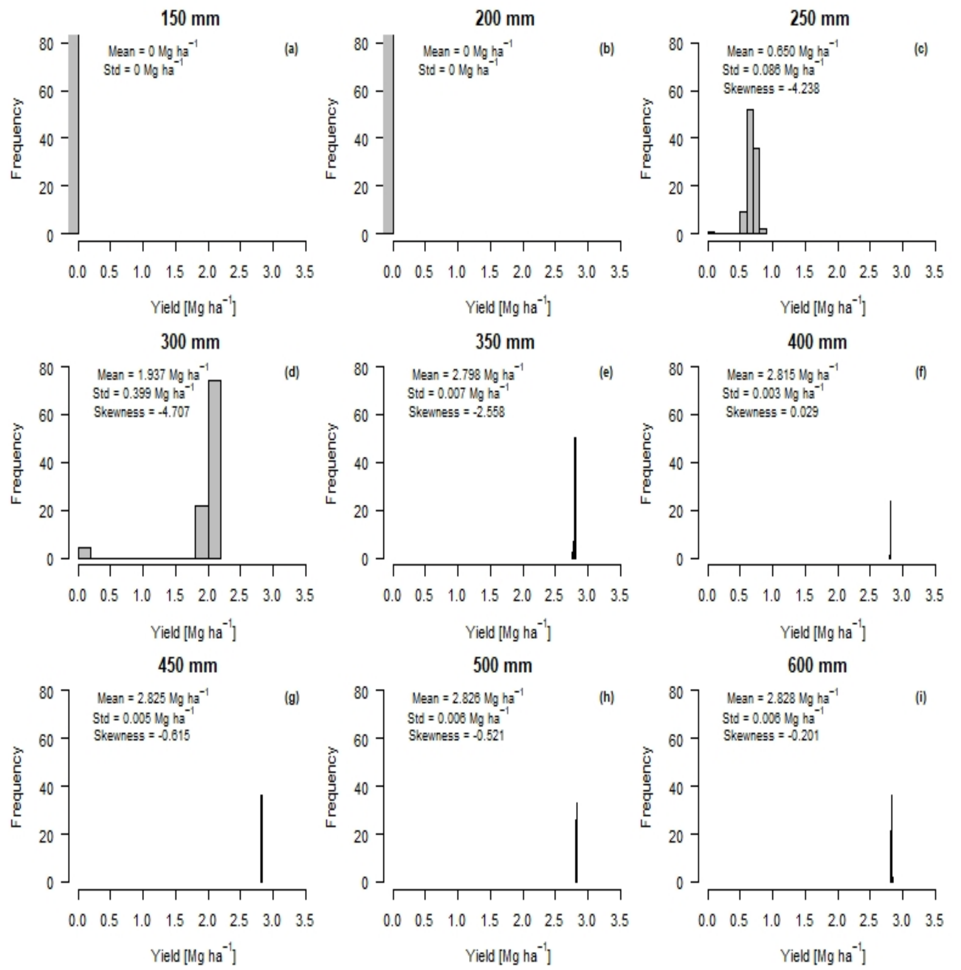

Figure B.35. Scenario 35

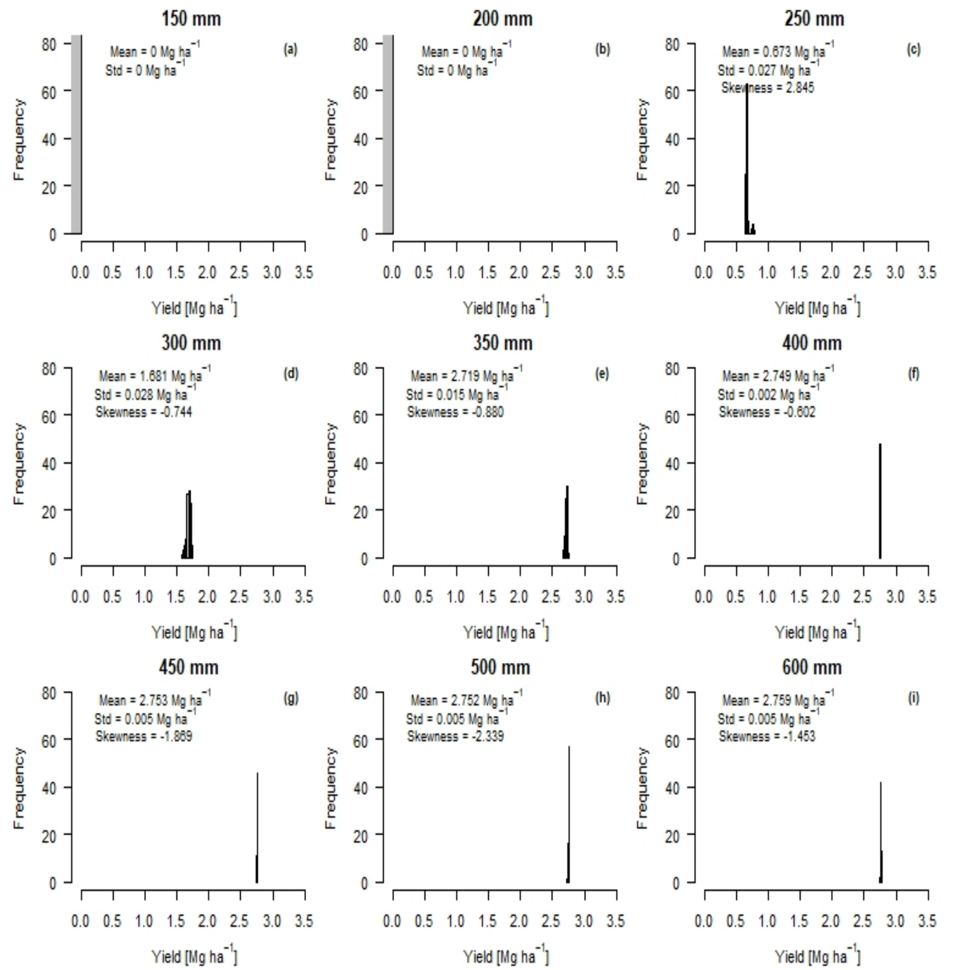

Figure B.36. Scenario 36

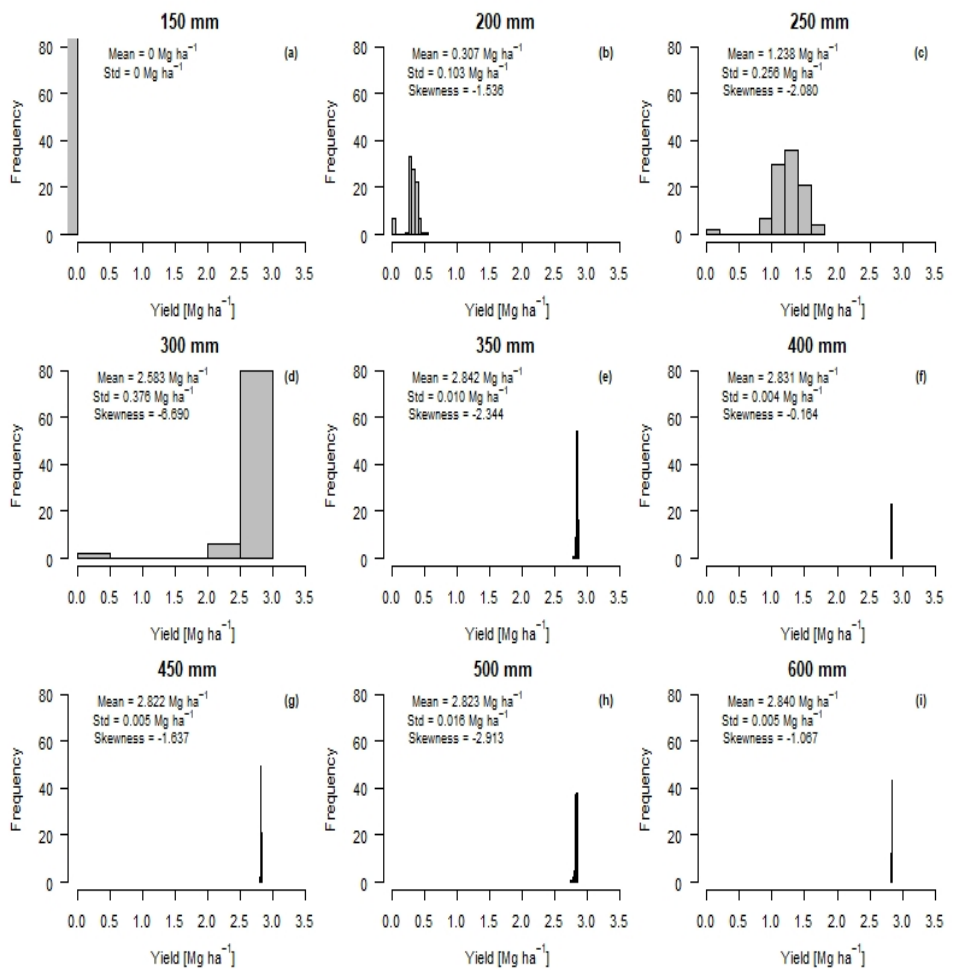

Figure B.37. Scenario 37

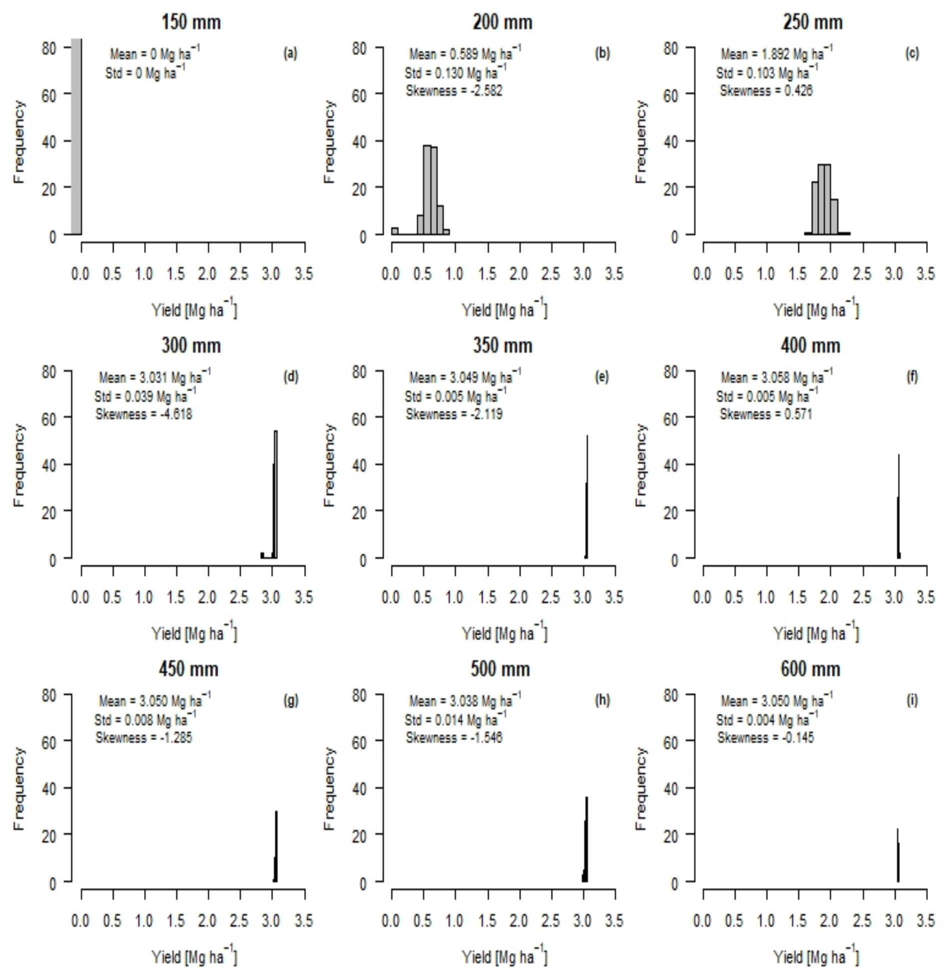

Figure B.38. Scenario 38

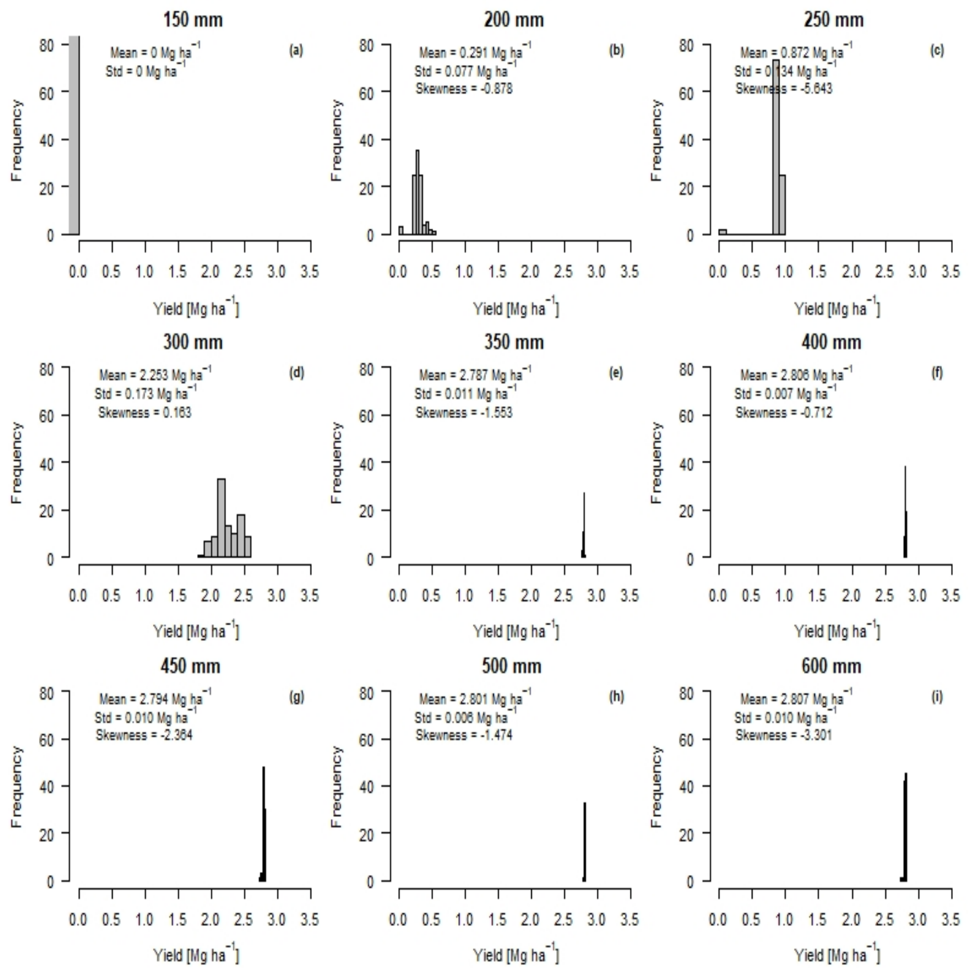

Figure B.39. Scenario 39

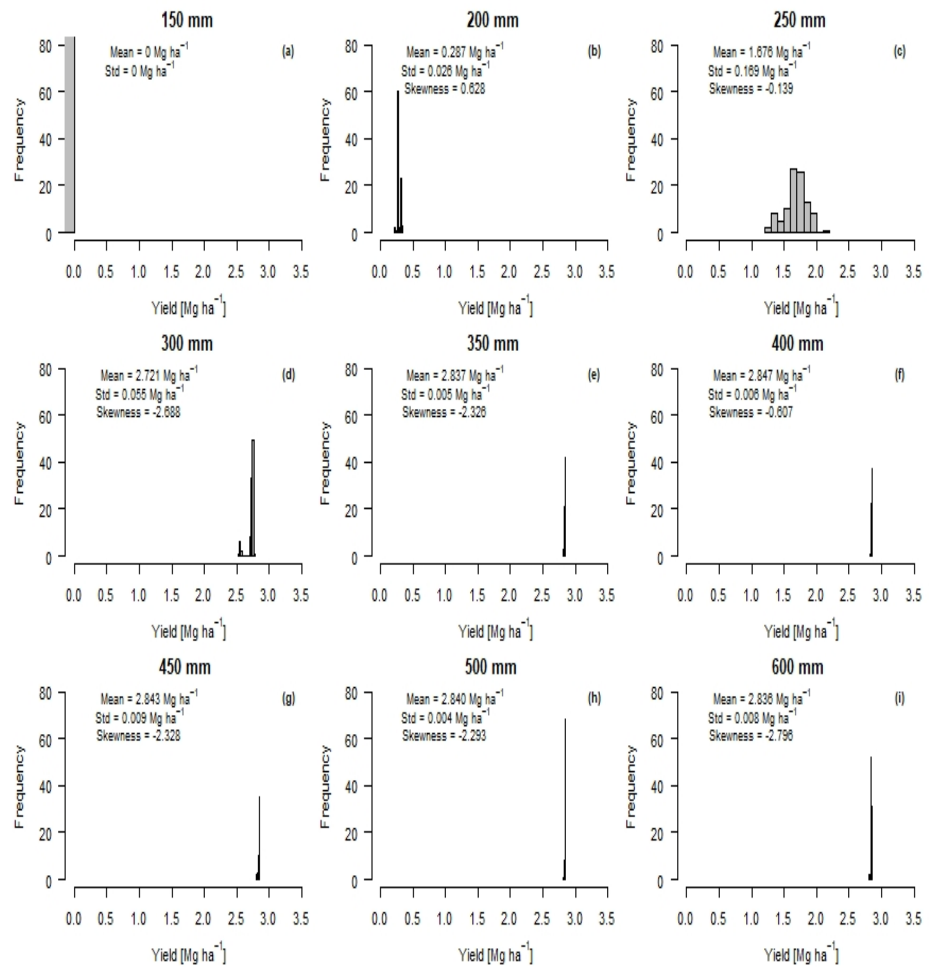

Figure B.40. Scenario 40

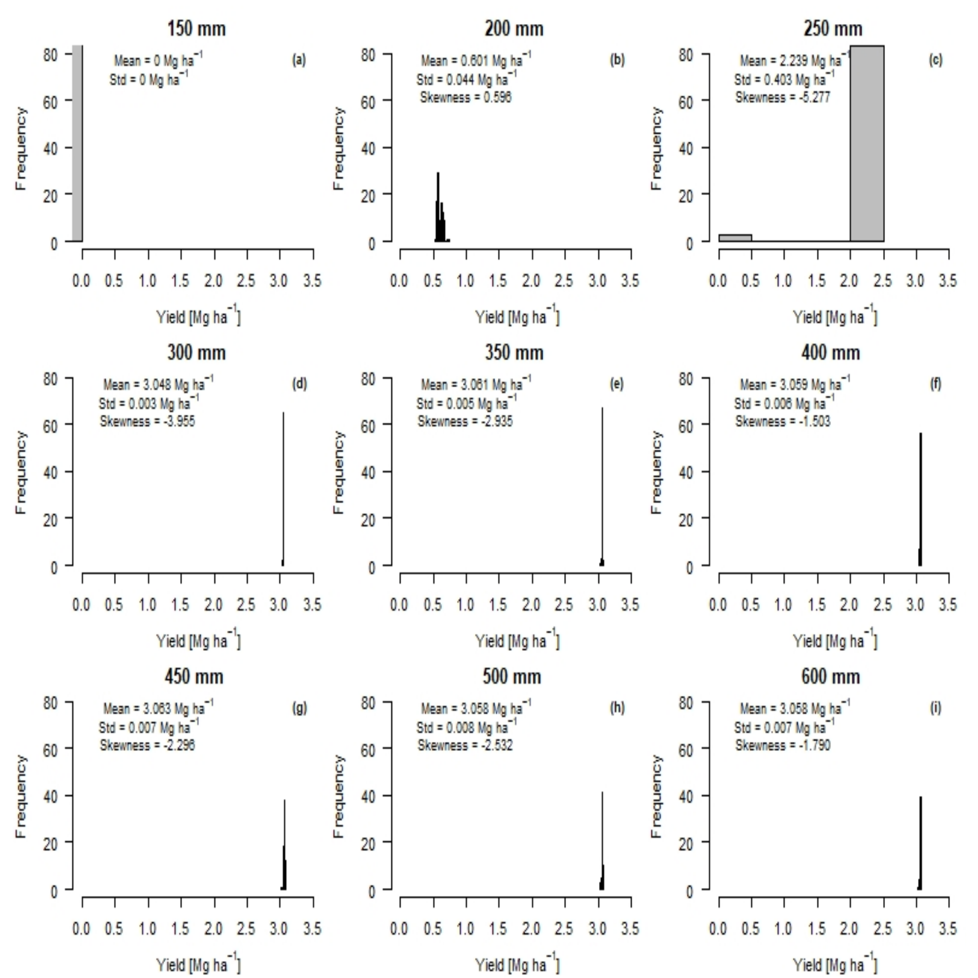

Figure B.41. Scenario 41

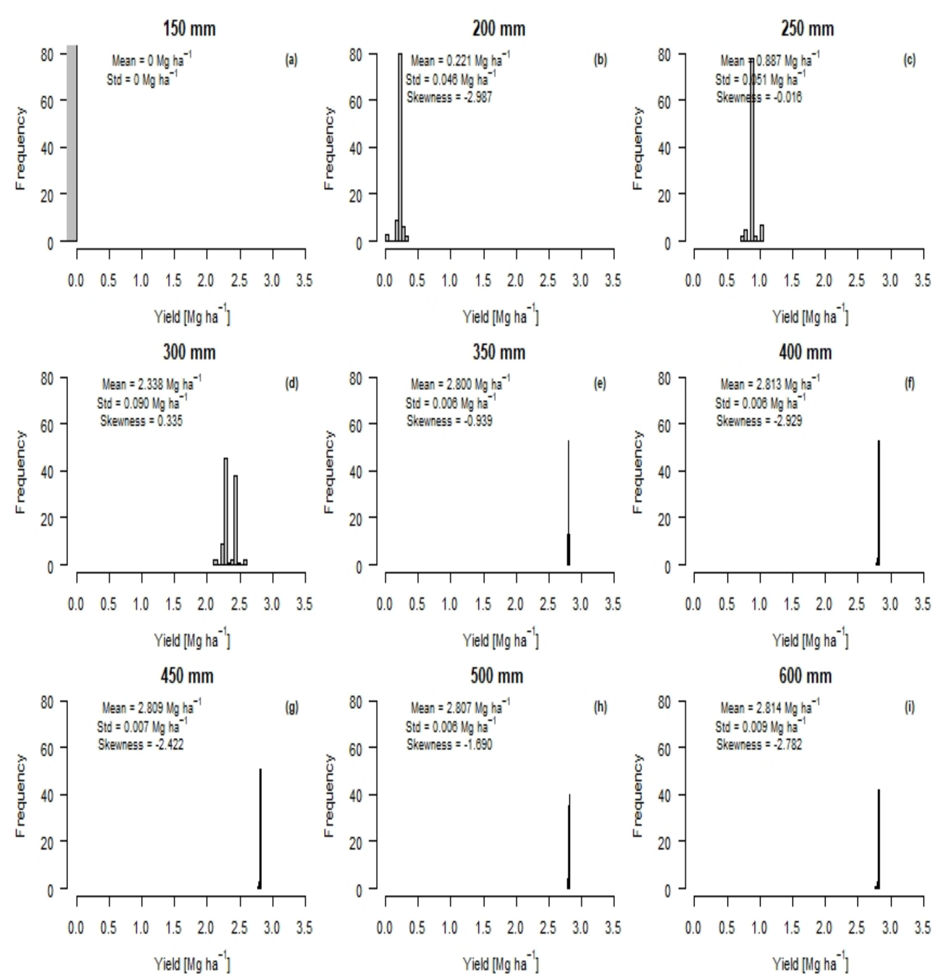

Figure B.42. Scenario 42

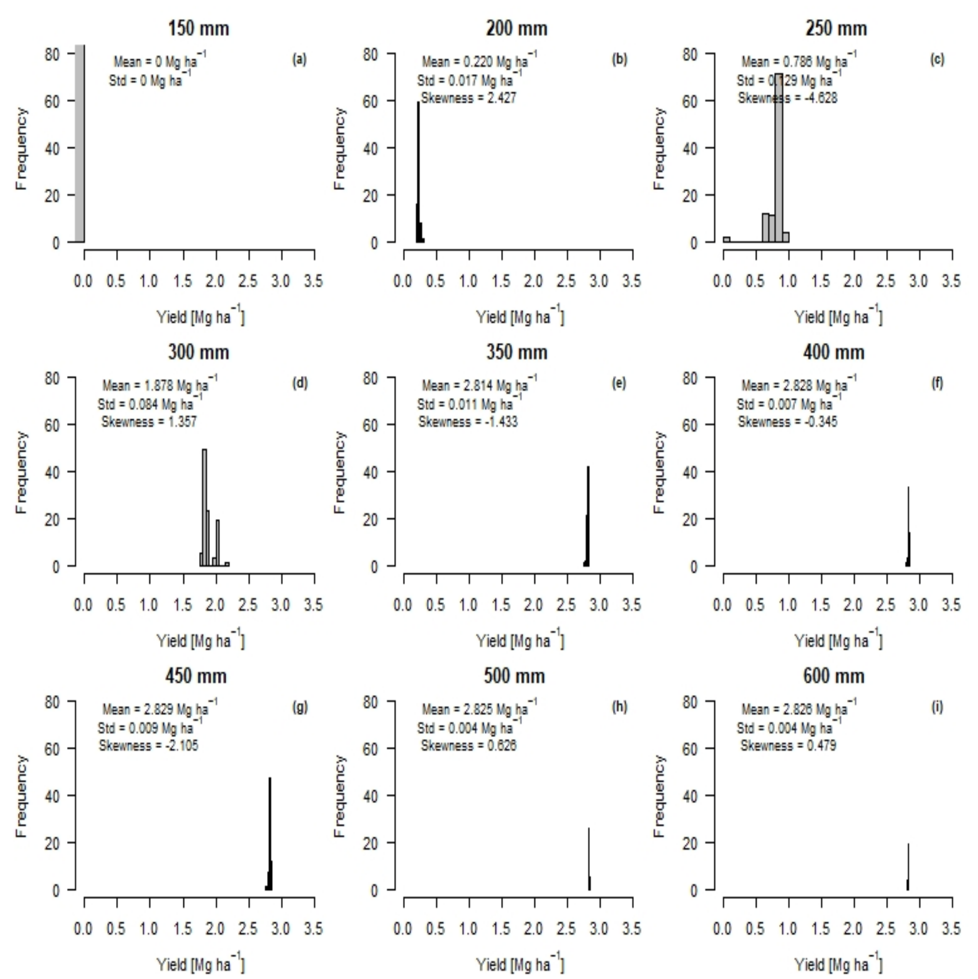

Figure B.43. Scenario 43

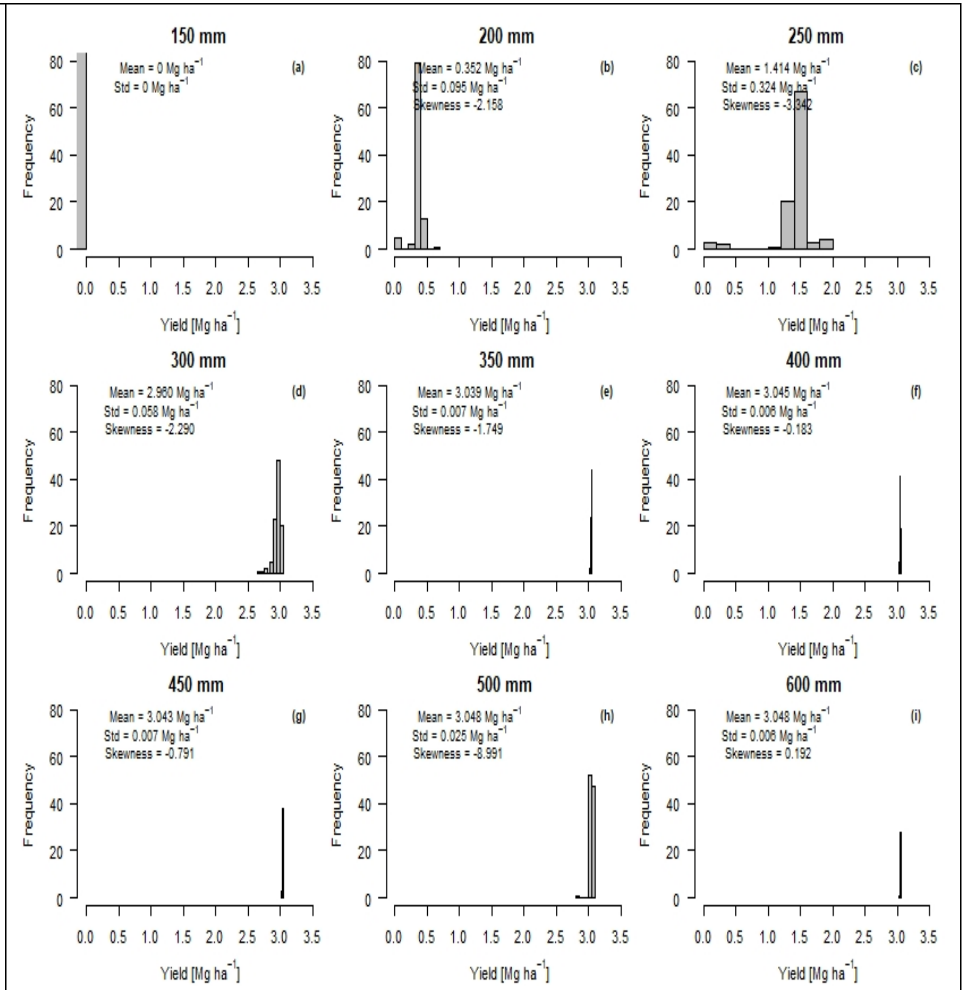

Figure B.44. Scenario 44

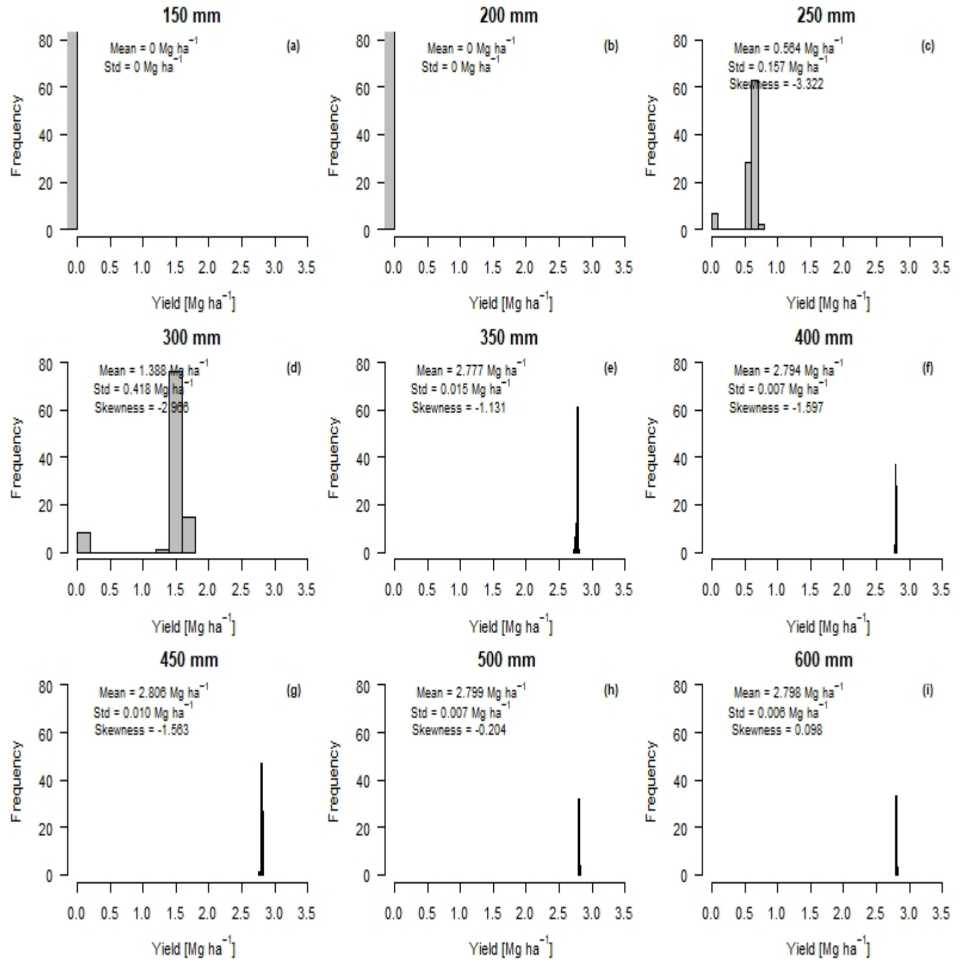

Figure B.45. Scenario 45

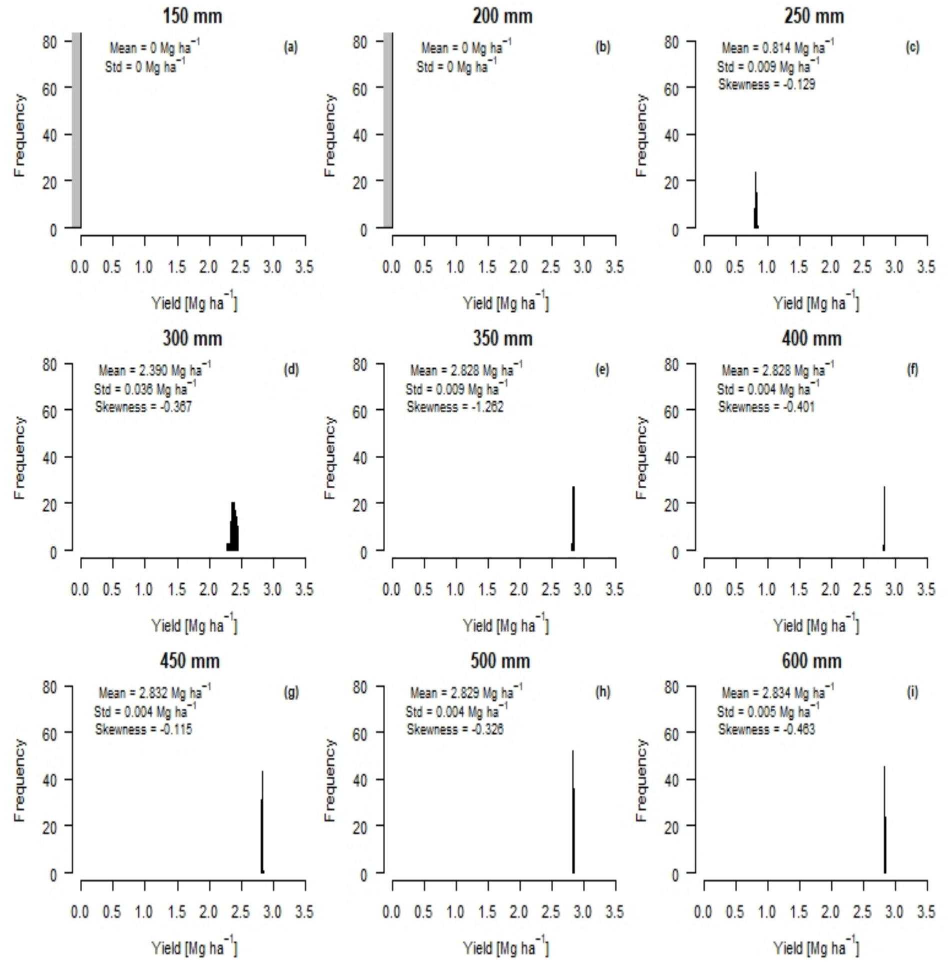

Figure B.46. Scenario 46

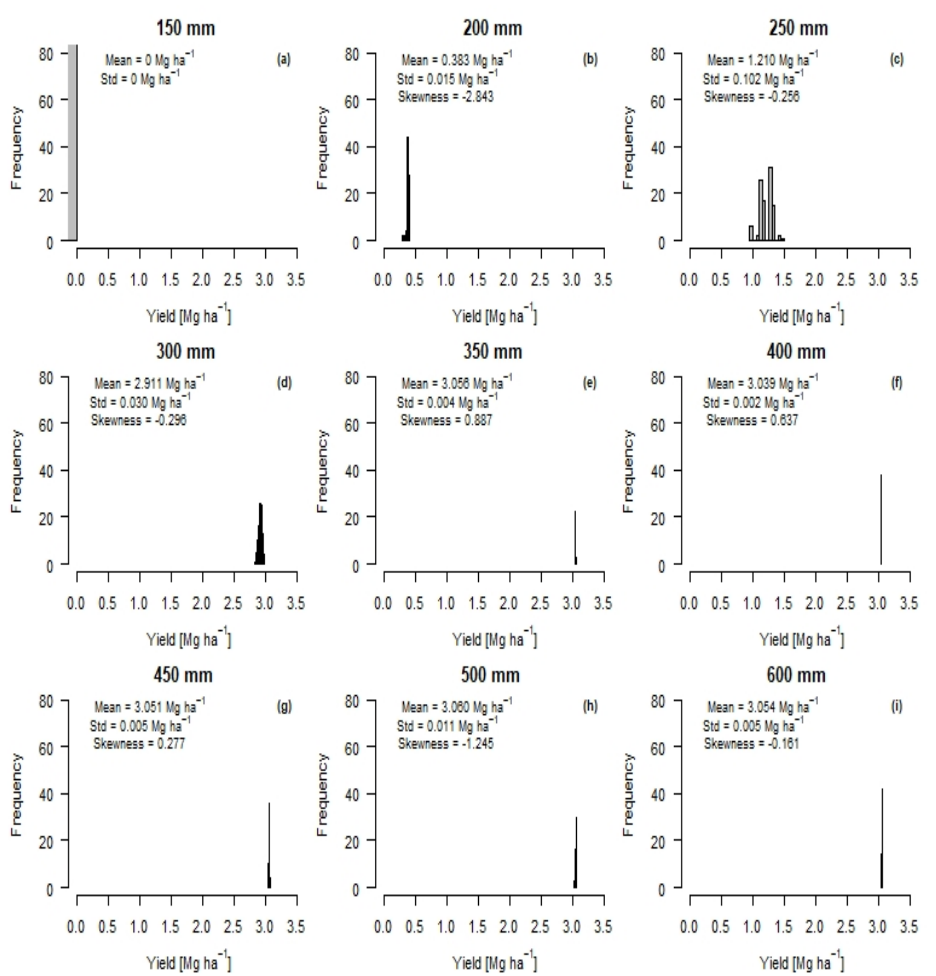

Figure B.47. Scenario 47

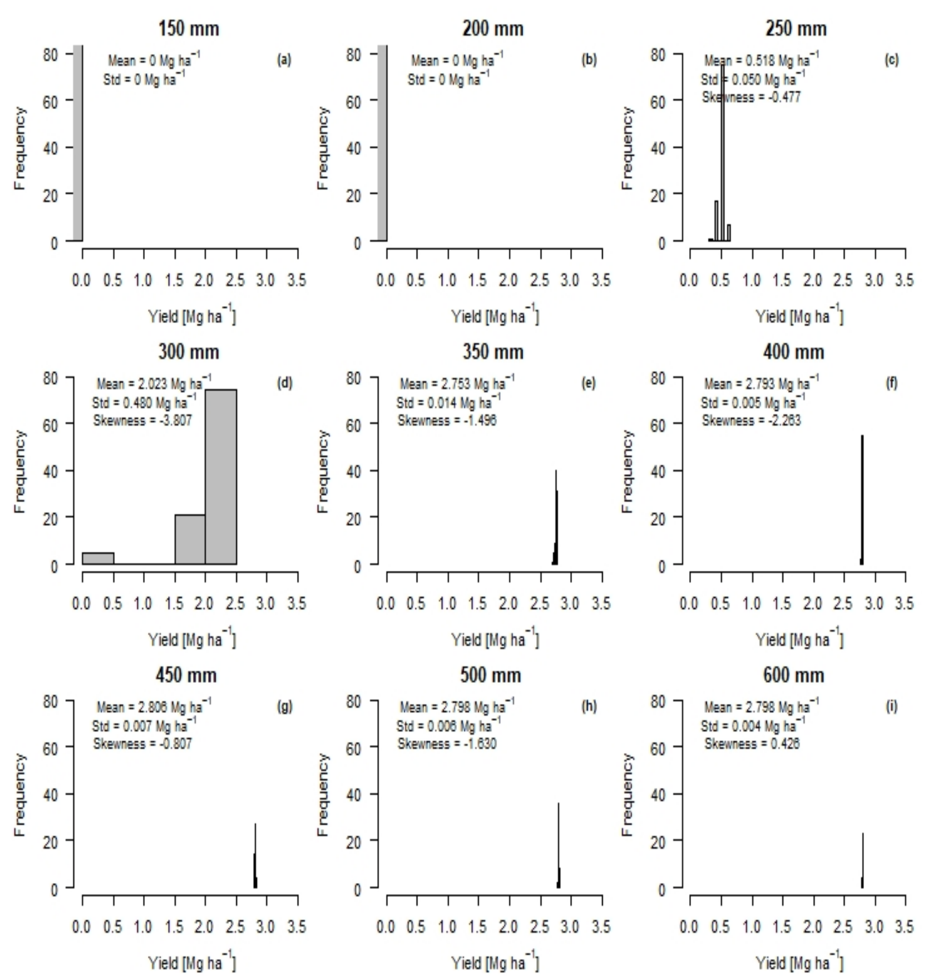

Figure B.48. Scenario 48

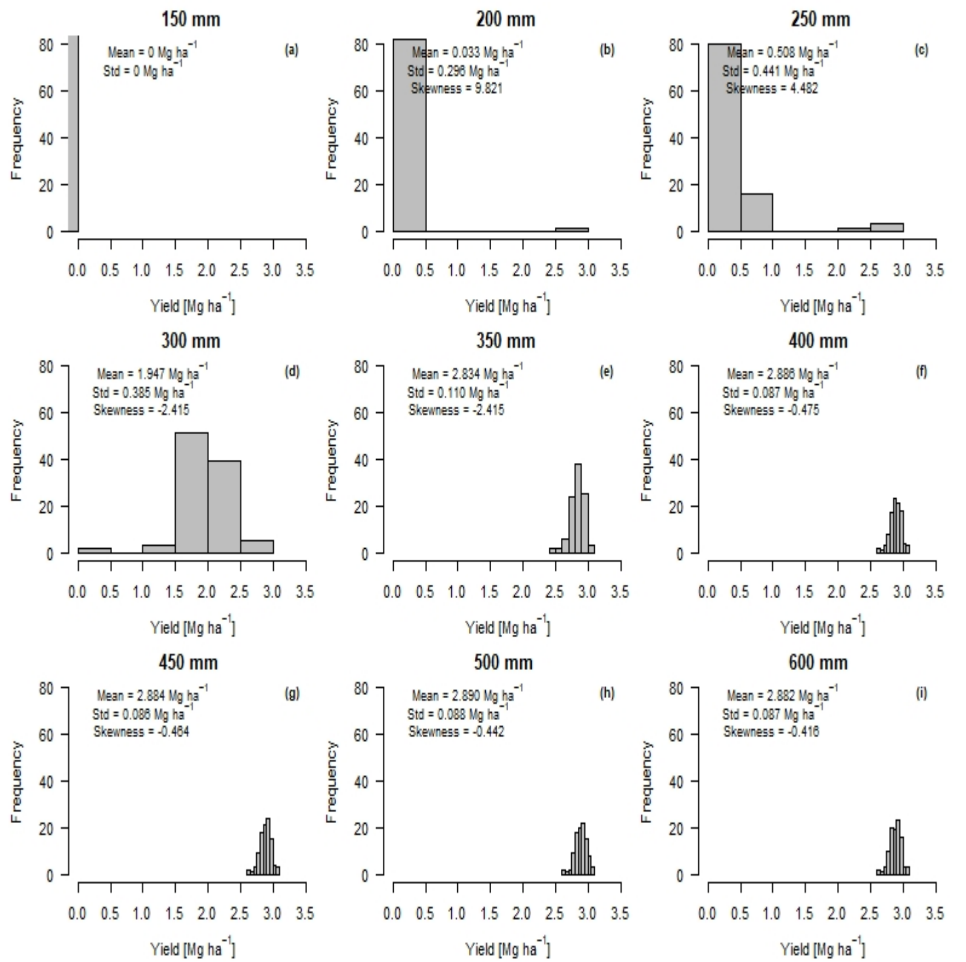

Figure B.49. Scenario 49

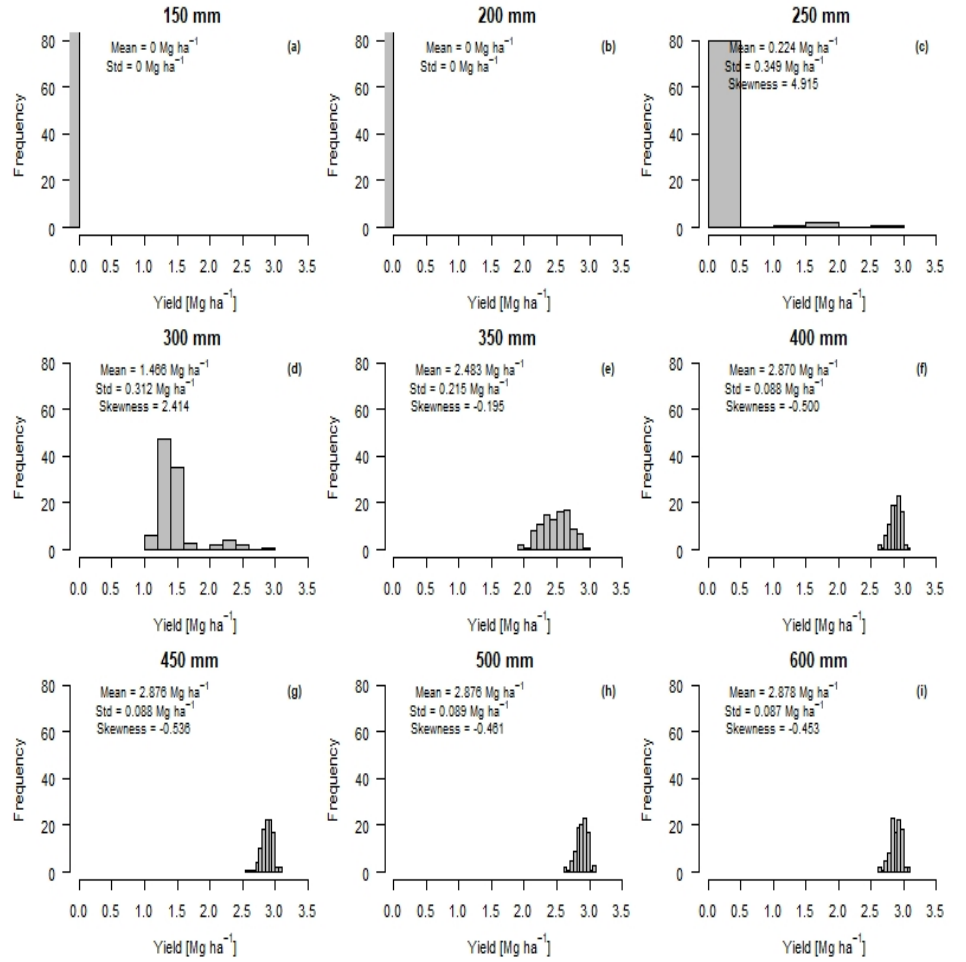

Figure B.50. Scenario 50

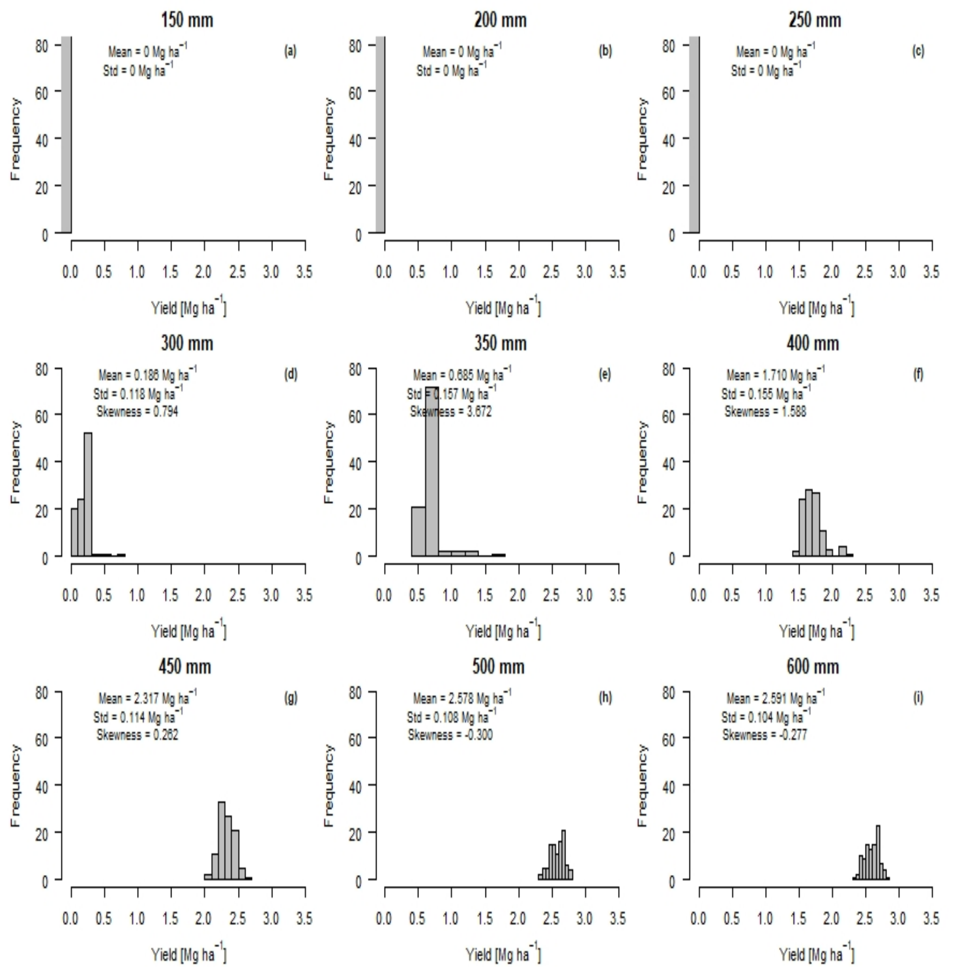

Figure B.51. Scenario 51

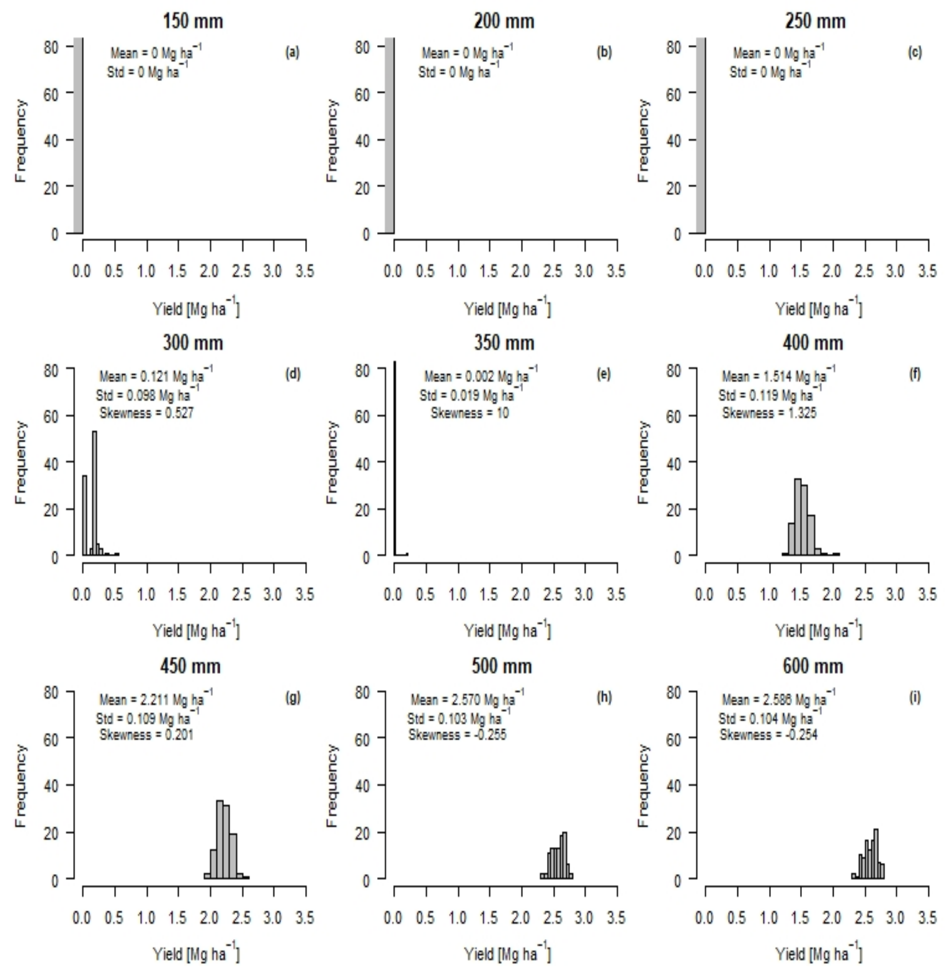

Figure B.52. Scenario 52

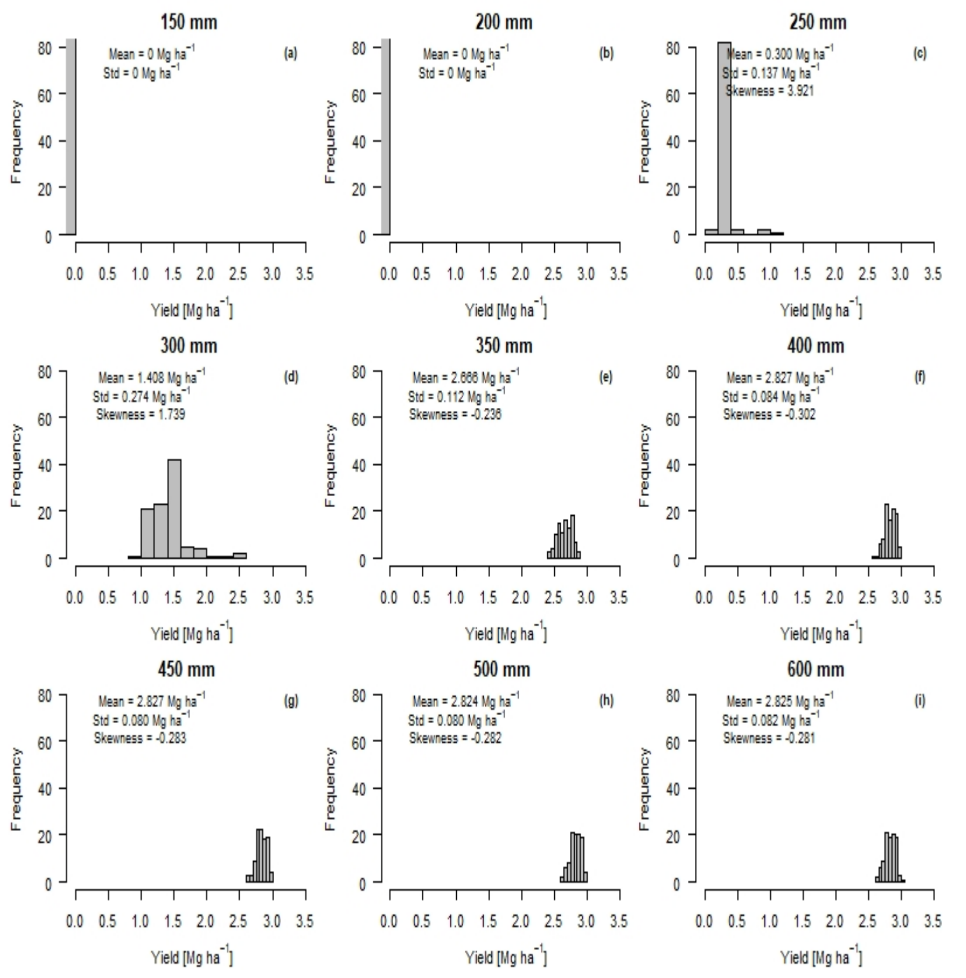

Figure B.53. Scenario 53

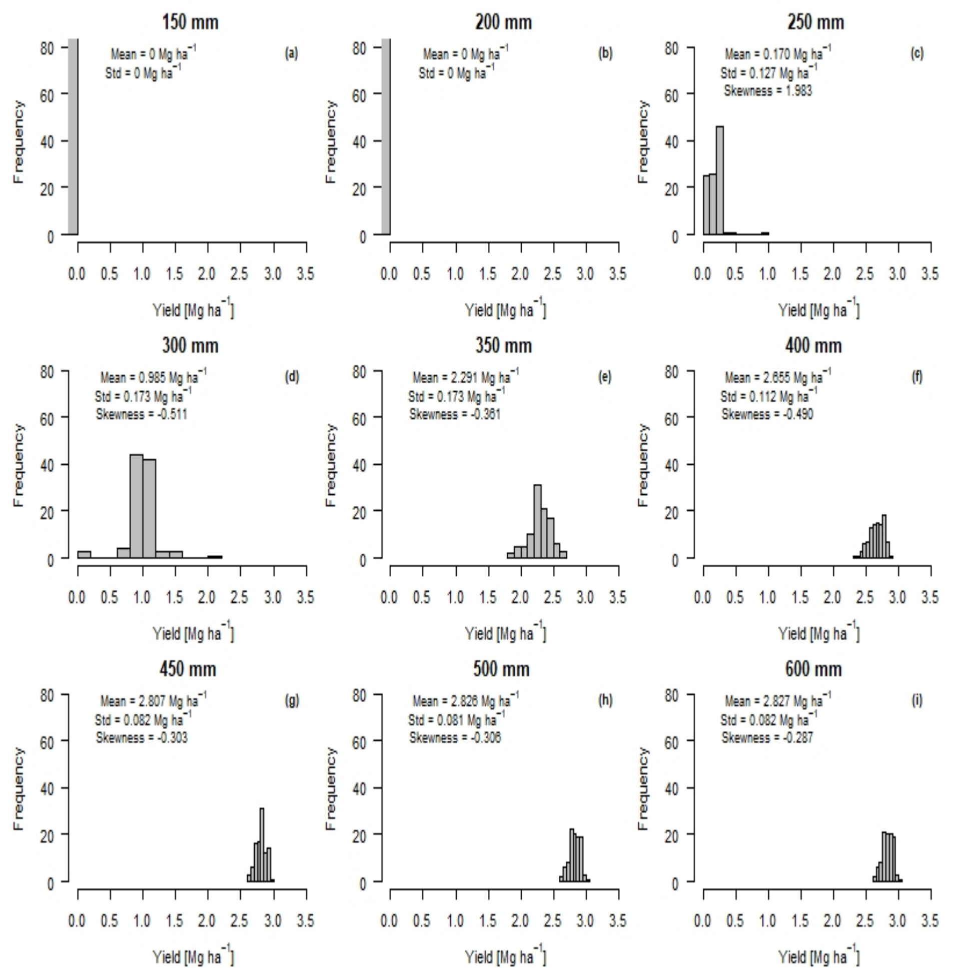

Figure B.54. Scenario 54

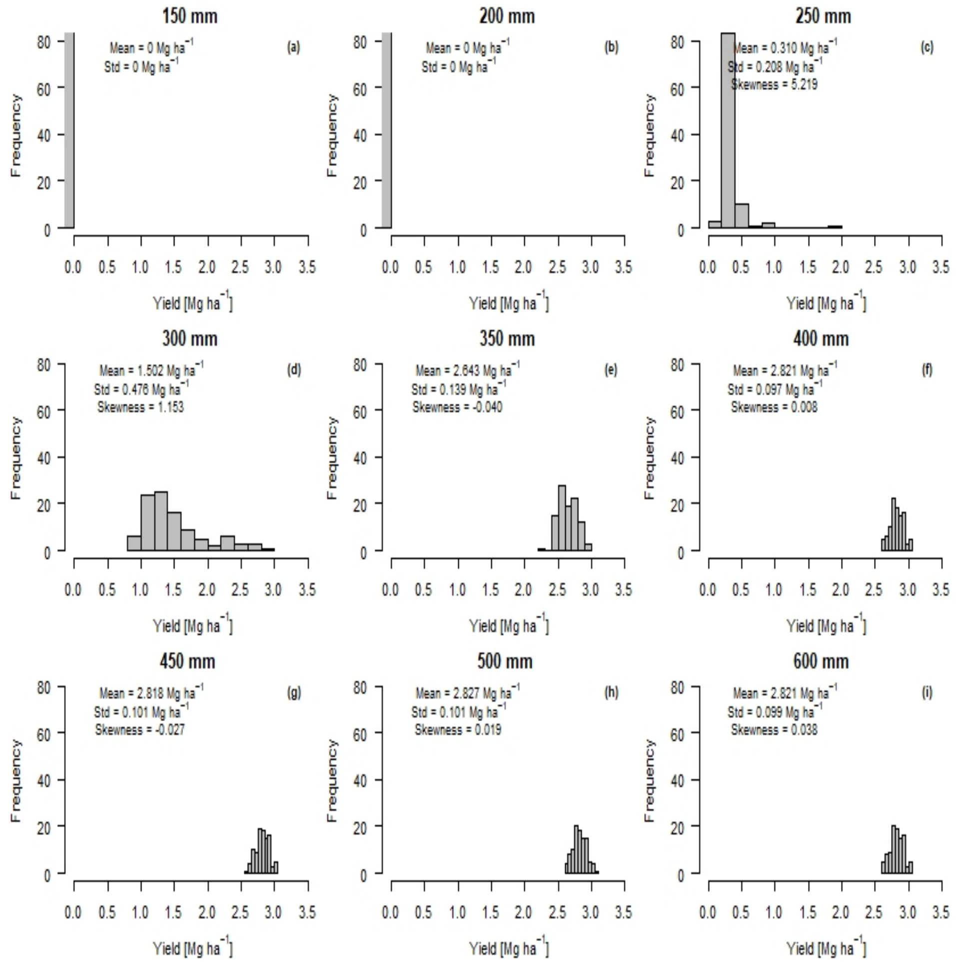

Figure B.55. Scenario 55

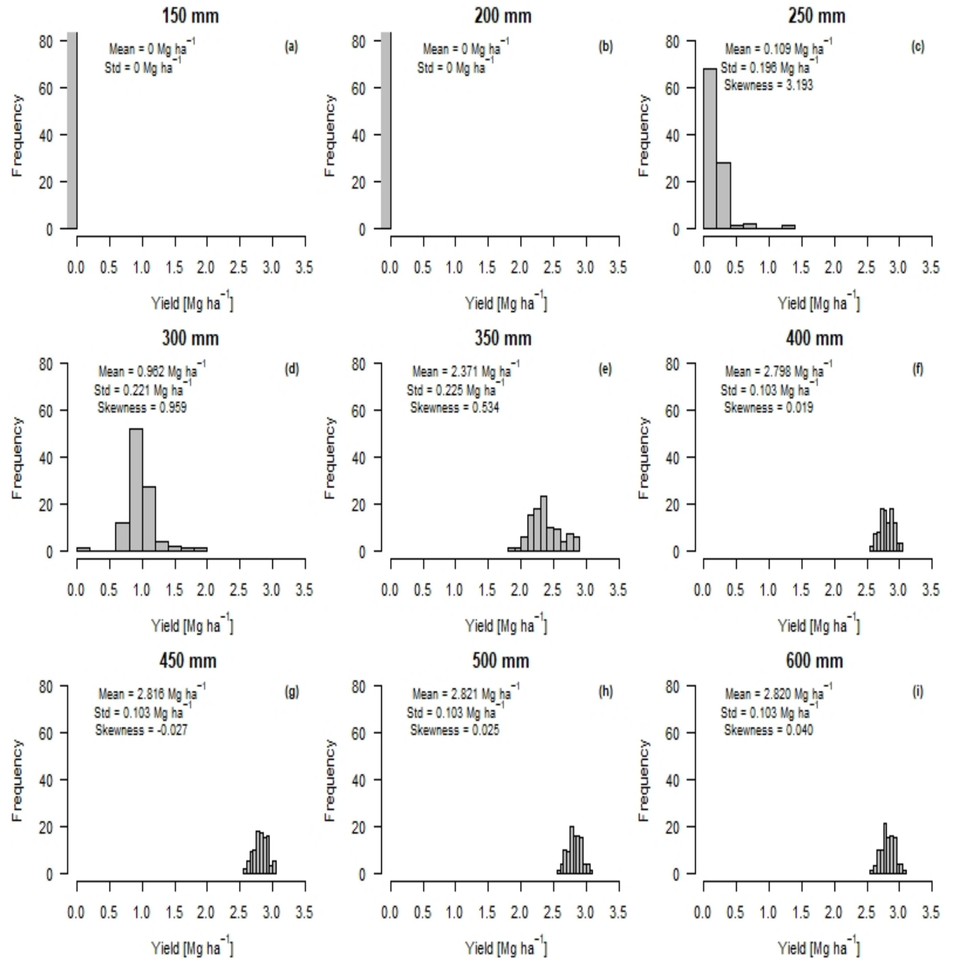

Figure B.56. Scenario 56